UTILISATION OF PROXIMAL SENSING TECHNOLOGY TO MAP VARIABILITY IN ONTARIO VINEYARDS

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"Αὖθις δὲ οἱ μὲν καὶ παρὰ δύναμιν τολμηταὶ καὶ παρὰ γνώμην κινδυνευταὶ καὶ ἐν τοῖς δεινοῖς εὐέλπιδες".

"Again, they (the Athenians) are brave beyond their power, and fearless beyond their judgment, and even when in danger they are optimistic".

Thucydides, The Peloponnesian War, 1.70.3

Αφιερωμένο στις πολυαγαπημένες μου γιαγιάδες Ελένη, Λίτσα και νονά-Μαρία.
Είστε για πάντα μέσα στην καρδιά μου...

ABSTRACT

Precision agriculture is a term used to refer to a suite of technologies used for the optimisation of production in agronomic crops. The overall goal of this study was to determine whether high resolution proximally sensed observations acquired by the GreenSeeker™ technology could be correlated with soil moisture, vine water status, yield components and grape composition, and whether temporally consistent relationships could be established. The research was carried out on three experimental sites involving two Riesling, two Cabernet franc and two Pinot noir blocks throughout the Niagara Region of Ontario (Canada). A grid of geolocated sentinel vines was chosen for each vineyard block. Data were collected three times during the growing season between fruit set and veraison [soil moisture, leaf water potential (ψ)], at harvest (yield components, berry composition) and in winter [vine size, winter hardiness (LT_{50})]. GreenSeeker™ observations were likewise collected from lag phase to just prior to harvest, through the calculation of Normalized Difference Vegetation Index (NDVI). Thereafter, relationships between vine water status, yield components and berry composition variables as well as data from the GreenSeeker™ were validated. Overall, higher NDVI values were associated with yield components and vine size, while lower NDVI values were correlated with better berry composition, suggesting that GreenSeeker™ is a practical tool for vineyard vegetative growth surveys, and for grape composition inferences. Clustering associations were made through *k*-means statistical analysis in conjunction with Moran's *I* spatial autocorrelation index; soil moisture followed by the NDVI had the strongest clustering patterns. The outcomes from proximal sensing technology allow opportunities to stream and compliment present agricultural practices towards higher accuracy and efficacy by means of exploiting the observed variation.

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ABBREVIATIONS

DGPS: Differential Global Positioning System

FVT: Free-Volatile Terpenes

GPS: Global Positioning System

GIS: Geographical Information System

IDW: Inverse Distance Weighted (Interpolation Method)

LAI: Leaf Area Index

LT_{50}: bud survival, temperature at which 50% of primary buds die, due to artificial freezing

NDVI: Normalized Difference Vegetation Index

NIR: Near infrared

PA: Precision Agriculture

PAB: Photosynthetically Active Biomass

PCA: Principal Component Analysis

PV: Precision Viticulture

PVT: Potentially Volatile Terpenes

RDI: Regulated Deficit Irrigation

RMSE: Root Mean Square Error

SVIs: Spectral Vegetation Indices

INTRODUCTION AND HYPOTHESES

Various factors contribute to the quality and quantity of grapevine production, all of which have a great input in shaping the quality and style of the end product (i.e. wine). These include soil characteristics, climate, vine vigour, yield, fruit composition, and exposure to pests and diseases. For as long as grapevines have been cultivated, grape growers and winemakers were well aware of their vineyards being quite inconsistent with land being the most apparent variable (Bramley 2010). Thus, viticultural practices aimed to alleviate the variability and vineyards were subdivided into areas of higher or lower quality, based on the growers' accumulated experience (Ledderhof et al. 2015).

Several studies have demonstrated that productivity under uniform management even at the single-vineyard scale, can vary as much as 10-fold (Bramley & Hamilton 2004), with soil being one of the major factors affecting the productivity of vineyards (Bramley 2001). Winemakers consider uniformity of the product delivered to the winery of equal importance to its sensory attributes in determining quality of the final product. It is easier to stream a uniform product towards the desired wine style formed by market demand, than try to change a product of different quality grades (Bramley 2010; Reynolds & Hakimi Rezaei 2014a).

The adoption of geospatial technologies in viticulture, including geographical information systems (GIS), remote sensing, and differential global positioning system (dGPS), has allowed for the investigation of vineyard variability and the wider integration of those technologies into the concept of precision viticulture (PV). The rapidly advancing field of geospatial technologies intends to obtain, examine, manipulate, store and visualize a wide variety of location-based data (Shellito 2014). The underlying principle behind the PV approach is that information about biophysical characteristics and performance of a vineyard, acquired by the use of geospatial technologies, can be beneficial to vineyard managers in decision-making processes. Furthermore, by allowing the identification of zones of characteristic performance, there is a greater potential in meeting standards for the intended wine with better control at the grape growing level.

In remote sensing, information is acquired from airborne or spaceborne platforms by recording the electromagnetic energy reflected or emitted from targets on the ground; when applied in viticulture remote sensing involves the view from above the canopy (Bramley et al. 2011; Shellito 2014). Proximal sensing technology operates under the same principles, with ground-sensing devices recording electromagnetic energy from the side of the canopy (Bramley et al. 2011). The overall goal of this research project was to test and verify the usefulness of proximal sensing technology, namely the GreenSeeker™, for making inferences with NDVI and important variables such as yield components, vine water status, and fruit composition in Ontario vineyards over two growing seasons (i.e. 2014-2015). Further, it was hypothesized that geospatial datasets acquired from GreenSeeker™ technology would be spatially correlated with measurements of soil moisture, leaf water potential (ψ), yield observations and berry composition characteristics.

Moreover, it was hypothesized that the validation of data acquired by GreenSeeker™ technology could be used to determine unique zones in terms of physiology, productivity, and berry composition and that spatial variability would follow temporally stable patterns. Only if spatial patterns are temporally consistent, would there will be potential predictive value in the data. Grape growers will be able to thereafter identify unique zones within vineyards without the use of airborne or spaceborne remote sensing technology, and subsequently implement appropriate management strategies and make wines of varying quality levels.

CHAPTER 1 : LITERATURE REVIEW

1.1 COOL CLIMATE VITICULTURE AND THE THEORY OF *TERROIR*

Viticulture is often conducted at geographic locations and under certain environmental conditions, which are typically considered unsuitable for most other crops (Holland et al. 2013). The impact of the physical environment on the development and ripening of grapes, along with the wine sensory characteristics attributed to those interactions, are usually described as the "terroir effect" (van Leeuwen 2010). When the term "cool climate viticulture" is used, it does not reflect actual cold temperatures, but refers to the ripening of the grapes under cool climate conditions, usually at the end of the summer or in the early autumn (September or October in the Northern Hemisphere, March or April in the Southern Hemisphere) (van Leeuwen 2010; van Leeuwen & Seguin 2006).

Terroir, a French word that encompasses the various interactions between the physical environment and grape vine cultivation, is profoundly expressed in cool climate regions (van Leeuwen & Seguin 2006). According to the International Organisation of Vine and Wine (O.I.V.), "vitivinicultural terroir" is the concept which takes into account all the interactions between the physical and biological environment along with the vitivinicultural practices. As a result, products (i.e. wines) with unique characteristics are created whose origins are easily recognisable (Organisation International de la Vigne et du Vin 2010).

While Seguin (1986) emphasized the importance of edaphic and geological characteristics to wine production and quality, the term was broadened to include the physical and chemical characteristics of soil, topography, climate, biology (i.e. rootstocks, cultivars, vine age), anthropogenic impacts, viticultural practices and oenological techniques (Holland et al. 2013; Reynolds & Wardle 1997; Seguin 1986; van Leeuwen & Seguin 2006).

The Niagara Peninsula, in Ontario, Canada is one of the cool climate regions of the world, in which the term "cool climate viticulture" is applicable. Vintners Quality Alliance of Ontario (VQA) is the regulatory authority of the province's "appellation of origin" system. The province of Ontario is comprised of three appellations: Lake Erie North Shore, Niagara Peninsula, and Prince Edward County, which are also divided into sub-appellations based on their differential terroir (Wine Country Ontario 2015b). Early ripening cultivars are widely planted; including Pinot noir, Gamay, Chardonnay, Riesling and Cabernet franc in order to optimise the chances of achieving correct ripeness (van Leeuwen & Seguin 2006; Wine Country Ontario 2015a).

The Niagara Region has experienced several glacial and interglacial events that eroded and shaped the layers of sedimentary rock and ancient reef structures of the Niagara Escarpment giving unique characteristics of complexity to the soils in this region. The soils range from imperfectly drained silty clay to moderately well-drained sandy loam (Shaw 2005). The ideal conditions of soil complexity, diverse *terroir* and microclimate, have allowed more than 46 wine grape varieties to thrive across 5,700 ha and subsequently to create extraordinary wines (VQA Ontario 2015).

The Niagara Peninsula is positioned between the cooler waters of Lake Ontario to the north, the Niagara River to the east and Lake Erie to the south; the moderating effect of the water bodies produce warmer conditions during cooler seasons and lake breezes during warmer temperatures (Jackson 2008; Shaw 2005). This characteristic feature of the Niagara viticulture region favours the extensive cultivation of a wide range of grape cultivars. It covers 1,900 km^2 and extends ≈60 km from the Niagara River in the east to the city of Hamilton in the west (Willwerth et al. 2015).

The Niagara Escarpment is a topographical attribute in the Niagara Peninsula consisting of north-facing slopes of variable elevation and distance from the lake. Located approximately 5 to 10 km south of the Lake Ontario shoreline, the Niagara Escarpment runs parallel, sitting approximately 50 m to 100 m higher than its northern surroundings (Willwerth et al. 2015). The Niagara Escarpment has a great influence on the winds and temperature of Lake Ontario serving as a shelter belt and creating distinctive climate characteristics (Shaw 2005).

1.2 VINEYARD VARIABILITY

Extensive research has been conducted to identify vineyard variability in terms of soil texture, moisture and depth, as well as vigour, yield, and fruit composition and its subsequent impacts on the produced outcome (i.e. wine of variable quality and price points). Studies seek to provide the grape industry with accurate data, so the viticultural and oenological practices are streamed according to ideal optimisation of the wines' potential, while taking advantage of the natural environmental factors and terroir.

In a study conducted over several vintages (i.e. 4 yr) in blocks planted with Cabernet Sauvignon, Merlot and Ruby Cabernet in Australia, each under uniform management, it was demonstrated that grape yield was quite variable (i.e. 2 to 20 t/ha), even within the same vineyard block. In Coonawarra vineyards in particular, the driver of this variation was the soil depth (Bramley & Hamilton 2004). Variation between years in terms of fruit quality indices showed temporal consistency, while the intra-annual variation (i.e. within field) was stronger for some variables, such as phenolics, as indicated by the variable "spread" (Bramley 2005; Bramley & Hamilton 2004). Hence, the temporal stability of vineyard variability patterns strongly suggest the implementation prospect of "zonal management" strategies based on variation in yield along with the potential economic benefits of such strategies (Bramley 2005; Bramley & Hamilton 2004; Bramley et al. 2005).

In a Spanish Pinot noir vineyard, when the parcel was divided into two clusters of different yields, yield was not only variable within the parcel, but also the patterns of spatial variability remained stable over three seasons. It was also concluded that the continuous *c*-means classification algorithm was more suitable in identifying zones, as opposed to *k*-means algorithm, by providing a more systematic zoning of the parcel over time (Arno et al. 2011).

1.2.1 VINEYARD VARIABILITY ASCRIBED TO SOIL PROPERTIES & TOPOGRAPHY

As viticulture has been practiced since the ancient years, it is evident that humans have indeed had a great influence on several aspects of the process. Unlike many other crop plants, the grapevine has low mineral and water requirements, allowing it to thrive on soils and hillsides unsuitable for other food crops (Holland et al. 2013; Jackson 2008). Therefore, especially in the past (i.e. Old World), it was a very common practice that fields reserved for grapevine cultivation were generally soils poorer in nutrients and located on slopes (Seguin 1986; van Leeuwen & Seguin 2006). Among all the factors influencing the establishment and prosperity of a vineyard, soil properties have very high importance with respect to determining vineyard variability. Thus, soil surveys are usually conducted prior to vineyard establishments to ensure the soil suitability, as well as on already established vineyards in order to assist in management and decision-making.

Grape vines can be cultivated in a wide range of environmental conditions, and soils. It is generally known that in soils high in nutrients and depth, vines tend to be high in vigour and yield (van Leeuwen & Seguin 2006). Furthermore, conditions inducing water deficit, such as clayey soils, improve the quality of the grapes, particularly when these conditions take place early in the growing season and with modest intensity (van Leeuwen et al. 2004). Bramley & Lanyon (2002) showed that variation in yield is primarily influenced by variation in plant water availability in the root zone, which is simultaneously linked to soil depth and topography (Bramley & Lanyon 2002). However, better wines typically come from the least fertile soils (van Leeuwen & Seguin 2006).

The relevance of soil physical properties (architecture, structure, porosity, and permeability) to vine water availability and subsequently to quality of terroirs was initially established by Seguin (1986). He demonstrated that in poor, free draining soils of Haut-Médoc (Bordeaux, France) rooting depth is the factor affecting red wine production, as it controls vine water uptake conditions. Moreover, when three major aspects of terroir were investigated all at the same time - climate, soil, and cultivar, it was found that soil had a greater influence on vine development and berry composition than the cultivar, while it was largely linked to vine water stress (van Leeuwen et al. 2004). Even when the main grapevine hydraulic mechanisms were investigated in terms of influencing vine/berry interactions, it was determined that water availability in the soil supersedes genetic variability of cultivars (Tramontini et al. 2013). Likewise, another study showed that different soil types confer different vigour levels (Fraga et al. 2014). However, very high-quality wines are grown on a wide variety of soils and therefore, the conclusion on the best possible combination of soil texture, depth and mineral supply for the intended wines is not simple (van Leeuwen 2010).

Soil moisture and composition confer modifying effects on vine development and fruit ripening by regulating the mineral availability in the soil, water uptake conditions, as well as the rooting depth and temperature. Soil depth and soil physical properties are the major causes of heterogeneous soil water availability within vineyards (Acevedo-Opazo et al. 2010b). When considering the term of terroir, van Leeuwen (2004) suggested that natural availability of soil nitrogen is important and highly dependent on soil type. Yet, for other minerals no direct relationship as to their effect on vine development and grape quality could be established - only if no excess or deficiency is observed (van Leeuwen et al. 2004). In another study, the potential relationship among manganese nutrition and grape phenolics was highlighted, and therefore detailed management procedures were recommended to achieve best results in grape yield and quality (Bramley 2001; Bramley & Janik 2005).

Bramley (2003) demonstrated that in a Clare Valley vineyard (range of elevation: 13 m) variation in yield was being variably affected by soil and groundwater salinity (Bramley 2003). The lower lying parts of the vineyard block, and the areas with closer proximity to a surface water dam used for irrigation, showed the least productivity in terms of yield, because groundwater salinity was high in those areas (Bramley 2003).

1.2.2 VINEYARD VARIABILITY ATTRIBUTED TO WATER METRICS

Water is one of the most important factors for grape vine growth and development; roots are using water as "coolant", while leaves as a means of eliminating overheating through evaporation (Jackson 2008; Acevedo-Opazo et al. 2008). Under water deficit conditions, when water loss cannot be replaced by the root system, the leaves' stomata close, and the metabolic activity in plant tissues slows down (Jackson 2008). In the event that water deficit conditions continue, water loss through the cuticle results in cell plasmolysis and death (Jackson 2008). Soil water content, i.e. water acquired from the soil, has been extensively demonstrated to have a great impact on crop yields, fruit composition, and overall wine quality (Seguin 1986).

Concurrently, depending on the soil depth and type, the rooting system develops differently and that affects the mineral nourishment and the water supply to the vine (Seguin 1986).

While seeking a method for assessing water in plant tissues, Scholander et al. (1965) developed a pressure bomb technique for the measurement of water potential. The theory underlying this technique is that under conditions of water deficit, there is an increasing tension in plant tissues (water potential; ψ), as water cannot be replaced by the roots in the same rate it is evaporating from the leaves (Shackel 2015). As stated in the protocol (Scholander et al., 1965), leaf stems are inserted into an airtight pressure chamber connected to a pressurised supply of nitrogen. The hydrostatic pressure required to achieve water exuding from the sap is measured, and is ideally equal to the pressure in the stem (Scholander et al. 1965). Sap pressure is normally negative during transpiration, ranging from -4 or -5 bars (-0.4 to -0.5 MPa) in a damp forest to -80 bars (-8.0 MPa) in the desert (Scholander et al. 1965).

In grape vine research, leaf ψ is an extensively documented variable indicative of the plant water status and subsequently stress and is measured by the pressure chamber technique developed by Scholander et al. (1965) and later expanded by Turner (1988). The following units of pressure most commonly represent vine water status: Bar (1 Bar = 14.5 pounds per square inch) and the Megapascal (1 MPa = 10 bars), where 1 Bar = 0.1 MPa. When leaf ψ values drop to < -1.0 MPa, the grapevines are under water deficit (Ojeda et al. 2002). Similarly, in a comparative study among the different types of leaf ψ, the midday leaf ψ ranged from –0.7 MPa (low water stress) to –1.8 MPa (high water stress) (Williams & Araujo 2002). Implementation of irrigation can be applied by measurement of vine water status over time (Acevedo-Opazo et al. 2010b; Williams & Araujo 2002).

In a *terroir* study conducted in Nemea (Peloponnesus, Southern Greece) on unirrigated vines, vine water status measured by pre-dawn leaf water potential measurements showed correlations with most viticultural and oenological variables (Koundouras et al. 2006). More specifically, low vine water status provoked by the soil and high temperature climatic parameters in the area contributed to the early ripeness of the berries and sugar accumulation, along with concentration of anthocyanins and phenolics in berry skins and wines. Sensorial analysis identified the wines made from different water status vines (Koundouras et al. 2006).

When unirrigated grape vines encounter water deficit conditions, there is a decrease in yield and berry size, and an increase in total phenolics, which leads to lower yields, but to higher quality grapes (Koundouras et al. 2006; Sivilotti et al. 2005; van Leeuwen & Seguin 2006; van Leeuwen et al. 2004). Koundouras et al. (2006) also showed that in water-stressed vines concentrations of soluble solids (°Brix) were elevated, while titratable acidity was low. In another study conducted in Cataluña (Spain), from vineyards with high water-holding capacity soils, which favour vine development, Grenache wines with low colour intensity and phenolics were produced (De Andrés-De Prado et al. 2007). Sensorial analysis identified the attributes given by the different soil types in the wines tested (De Andrés-De Prado et al. 2007).

The duration of water stress greatly impacted vine size, yield, and berry composition in Gewürztraminer; higher volatile terpenes (both FVT and PVT) accumulated in berries when deficit irrigation was applied at veraison in comparison with early and mid-season applications (Reynolds et al. 2005). In Riesling berries, water status regions were correlated with higher monoterpenes concentrations (Willwerth et al. 2010), and in Cabernet franc with higher anthocyanins and phenols (Hakimi Rezaei & Reynolds 2010a, b), thus indicating that mild water stress (moderately irrigated vines) may have a generally positive influence on grape composition and desirable wine sensorial attributes (Reynolds et al. 2007a).

A study about vine water status and sensory characteristics in Pinot noir identified sensorial differences attributable to low water status zones, such as black currant and earthy aromas, concluding that differences were highly dependent on terroir and vintages (Ledderhof et al. 2014). An extensive study in ten Cabernet franc blocks in Ontario, Canada showed that soil moisture and vine water status zones were temporally consistent in most vintages and sites, while establishing strong correlations among these variables with yield and vine size (Reynolds & Hakimi Rezaei 2014a,b). Temporally stable correlations were determined between soil moisture and vine water status with wine quality indicators, for instance low water status zones were associated with higher °Brix, colour intensity, anthocyanins and phenols (Reynolds & Hakimi Rezaei 2014c). In Oregon Pinot noir, low vigour zones showed some spatial patterns in regards to anthocyanin and phenolic composition, yet were vintage and site dependent; wines from low vigour zones had higher concentrations in anthocyanins and pigmented polymers, while sensorial analysis confirmed differences in astringency, bitterness, sour and sweet tastes, earthy and chemical attributes, and heat (Cortell et al. 2007a,b; 2008).

Although research has confirmed analogous positive effects on grape composition under moderate water deficit situations (Ojeda et al. 2002), the main priority for grape growers remains to achieve high quality crop yield, which in turn will lead to high quality wines. Thus, the optimal vine water content and soil moisture may need to be implemented with irrigation, when natural precipitation is not adequate (Holland et al. 2013; van Leeuwen & Seguin 2006). Prolonged vine water stress can have many negative effects, including diminished winter hardiness, delayed maturity, and reduced yields (Reynolds 2010). In order to achieve optimisation of wine quality components and impose water deficit situations, the approach of implementing regulated deficit irrigation (RDI) has been adopted (Ojeda et al. 2002). Successful and precise application of RDI is directly associated with accurate vine water status monitoring (leaf ψ, as a vine physiological index) (Acevedo-Opazo et al. 2010a; Taylor et al. 2010).

1.2.3 VINEYARD VARIABILITY IMPARTED TO WINE ATTRIBUTES

Recently research has focused on identifying unique portions of vineyard study plots, some < 1 ha, that might be capable of producing extremely high-value wines, based on yield, vine size, or water status-based quality levels (Bramley et al. 2011a). They analysed -both chemically and sensorially- small lot wines produced from uniformly managed zones and demonstrated that wines showed clear differences. When relationships among sensory characteristics, chemical attributes, and soil, grape and vine attributes were explored, many significant relationships were established, such as an apparent association with the soil extractable iron (Fe) and "red confection" sensory aroma attribute, providing supporting evidence that the terroir of those zones is different.

Shiraz wines from the Grampians region of Victoria, New Zealand are famous for their distinctive "spicy" and "peppery" aroma and flavour, conferred by a grape-derived chemical compound called "rotundone" (Scarlett et al. 2014). They investigated spatial variability of the "pepperiness" character as well as whether selective harvesting would be able to manipulate the intensiveness of that particular character. By utilisation of both topographic and soil maps, "rotundone" was found to be spatially variable, and variability was temporally consistent across the two years of the study, showing the expression of terroir.

Reynolds et al. (2007b) attempted to address the issue of direct influence of soil texture and vine vigour on yield components, berry, must and wine composition, and wine sensory attributes. In spite of the fact that several sensory attributes were correlated with vine size (i.e. cane pruning weight) and soil texture, no temporally consistent relationships could be established across four vintages (Reynolds et al. 2007b). A study about vine water status and sensory characteristics in Pinot noir identified sensorial differences attributable to low water status zones, such as black currant and earthy aromas, concluding that differences were highly dependent on terroir and vintages (Ledderhof et al. 2014). Sensorially different wines were produced from previously identified product categories in a uniformly managed Riesling vineyard, indicating that some terroir elements can be handled (Bramley & Hamilton 2007).

1.3 PRECISION VITICULTURE

It is widely known, among the grape grower industry and viticulturists, that vineyards show high degrees of variability. Technological advances in geospatial technologies, such as Global Positioning Systems or GPS, remote sensing (including proximal sensing), and geographical information systems or GIS have permitted the use of these technologies in viticulture in order to create information products that can be used to inform vineyard management decisions. The currently existing equipment to accurately and rapidly observe, measure, and evaluate the given vineyard variability has not found wide applicability yet, since the majority of commercial vineyards nowadays are still treated as homogenous.

Geospatial technologies can input to farming practices information acquired by devices that detect electromagnetic radiation i.e., visible, and near-infrared energy in order to achieve the concept of precision agriculture. When geospatial technologies are applied to viticulture, there is a focus on understanding the spatial and temporal variability in the production of wine grapes. The overall goal is to achieve ideal optimization of vineyard performance and to apply a precision viticulture approach to both viticultural practices and winemaking (Hall et al. 2003). Acquisition of airborne imagery started in 1994 in Australia among other places, initially as a research support tool for exploring variation in soil texture (Lamb 2000), rather than a commercial monitoring tool as it is regarded nowadays.

Currently, the increased availability of geospatial technologies has allowed their wide application in wine grape production regions, such as California (Johnson et al. 2003), Australia (Bramley 2005; Bramley & Hamilton 2004; Bramley & Janik 2005; Bramley & Lamb 2003; Bramley et al. 2005; Lamb et al. 2004a), New Zealand (Trought & Bramley 2011), Spain (Santesteban et al. 2013), Chile (Acevedo-Opazo et al. 2010a, 2013), France (Acevedo-Opazo et al. 2008, 2010b; Taylor et al. 2010) and in Ontario, Canada (Reynolds & Hakimi Rezaei 2014a-c; Reynolds et al. 2007b).

Precision viticulture is designed to allow grape growers to focus on the vineyard management at the multi-field scale (i.e., as almost each field within the vineyard is an isolated unit), instead of as a contiguous block. The viticultural practices are then targeted to manage heterogeneity in vine vigour and fruit composition, as opposed to having a uniform management (Bramley & Hamilton 2004; Bramley et al. 2005; Lamb et al. 2004b). Of fundamental importance for both grape growers and winemakers is that the fruit delivered to the winery is as uniform as possible, which meets their particular requirements for their intended final product (Bramley & Hamilton 2004; Bramley & Lamb 2003).

The precision viticulture approach is initially applied within the vineyard scale, where several observations are carried out (e.g. remote sensing, soil and plant tissue monitoring), followed by understanding the information acquired, assessing it and finally implementing more targeted handling systems, such as fertiliser, insecticide, or irrigation application (Bramley 2001, 2010; Bramley et al. 2003). As stated in Bramley et al. (2005), the definition of "selective harvesting" in the vineyard context is "the split picking of fruit at harvest according to different yield/quality criteria, with consignment to different product streams in order to exploit the observed variation in vineyard performance" (Bramley 2010; Bramley et al. 2005; Bramley & Hamilton 2004).

Lastly, all these new technologies aim to promote a vineyard management based on efficiency and quality of production (Matese & Di Gennaro 2015). Both remote and proximal sensing technologies are implemented to explore vineyard variability, with respect to soil and water status, nutrient availability, plant health and disease incidence (Matese & Di Gennaro 2015). Hence, precision viticulture focuses on the best exploitation of vineyard spatial variability, and addresses suggestions of modified management practices (Matese & Di Gennaro 2015).

1.3.1 REMOTE SENSING

Remotely sensed imagery provides information about mapping and monitoring vineyard canopy attributes at multiple resolution scales, often with spatial resolutions on the order of meters to centimeters, by detecting electromagnetic energy reflected from earth surface features (Bramley & Lamb 2003; Dobrowski et al. 2002; Hall et al. 2002). Generally, remote-sensing devices are operated from three different platforms including spacecraft, aircraft, and unmanned aerial vehicles or UAVs (Badr et al. 2015; Matese & Di Gennaro 2015). Spectral measurements in red and near-infrared (NIR) portions of the electromagnetic spectrum (EMS) are acquired by those airborne or spaceborne platforms and are thereafter processed in images of spectral vegetation indices (SVIs). The most commonly computed index for mapping variations in canopy density is the normalized difference vegetation index (NDVI), formulated as:

$$NDVI = \frac{NIR - red}{NIR + red}$$

where the red and near infrared (NIR) bands are used (Hall et al. 2008; Johnson 2003; Stamatiadis et al. 2006).

The theory underlying the NDVI calculation is that photosynthetically active foliage absorbs sunlight in the visible red and strongly reflects energy in the NIR portion of the EMS; this region is not detectable by the human eye (Dobrowski et al. 2002; Jollineau & Fast 2013). The NDVI value is a number between -1 and +1, and "quantifies the relative difference between the near infra-red reflectance peak and the red reflectance trough in the spectral signature" (Lamb 2000) and is considered sensitive to vegetation vigour and density (Jollineau & Fast 2013). When the area is densely vegetated, the NDVI value will be close to +1, while for non-vegetated objects, the value will be close to 0; negative NDVI values are seldom found in objects of agricultural relevance (Lamb 2000).

In remote sensing, the images acquired by multi-spectral optical sensors can be used to assess vegetation health and correlate with other plant status variables, such as yield and vine vigour (Shellito 2014; Mazzetto et al. 2010). Other photosynthetically active biomass (PAB) indexes, such as the plant cell density (PCD = NIR/red), have been recently introduced to quantitatively measure vine vigour; NDVI and PCD are associated with vine size (i.e. vine vigour) and are considered good indicators of healthy canopies (Bramley 2010; Lamb 2000).

While vine canopy area and density has been demonstrated to variably impact the quality and yield of wine grapes at different phenological stages, remotely sensed imagery is potentially capable of mapping different zones as well as predicting yield and quality (Hall et al. 2011). The spatial resolution of a sensor refers to the size of individual pixels per unit area in the field of view (FOV) of the sensor (Hall et al. 2008; Lamb 2000). The spatial resolution of a sensor is often defined as either low (large pixel sizes) or high (small pixel sizes). Higher spatial resolution imagery provides spectral reflectance information from either the grapevines or the inter-row spaces, while lower resolution reflectance information datasets predominantly include a combination of the grapevines and the inter-row spaces (Hall et al. 2008). Canopy reflectance (in the visible parts of the EMS) is variably affected by the photosynthetic pigments (such as chlorophyll a and b) and by the structural shape and water status of leaves in the near infrared (Matese & Di Gennaro 2015).

Since relationships among canopy reflectance and biomass production in vineyards have been established, the NDVI has been linearly associated with plant canopy leaf area index (LAI; m^2 leaf area/ m^2 ground area), and the amount of photosynthetically active radiation absorbed by the canopy. NDVI maps in conjunction with ground-based LAI measurements can be utilised for spatial interpretation in terms of infestation and disease, water status, fruit characteristics, and wine quality (Johnson 2003; Johnson et al. 2003). Those strong linear correlations between the NDVI measurements, acquired from the IKONOS satellite (4 m resolution), and ground measurements of LAI in different growing stages in a Napa Valley (California) red grape variety vineyard served as an irrigation scheduling tool (Johnson 2003).

Dobrowski (2002) demonstrated that the ratio vegetation index (RVI=NIR/Red) and the NDVI are linearly correlated to vertically shoot positioned (VSP) vine canopy density, using both aerial imagery (at the vineyard scale), and field spectroscopy practices (at the vine scale) (Dobrowski et al. 2002). In a California Cabernet Sauvignon vineyard, it was demonstrated that the RVI was strongly positively correlated with field-wide measurements of pruning weight density post-harvest (dormant pruning weight per metre of canopy) using an airborne imaging system (ADAR) of 0.6 m resolution (Dobrowski et al. 2003). The relationships remained constant for the two consecutive growing seasons of the study and relationships established in the first season were able to predict the vine size in the second study vintage (Dobrowski et al. 2003). High-spatial resolution multispectral images were used to subdivide a Chardonnay vineyard into small-lot vigour zones, whereby vigour zones were correlated with vine size, vine water status and grape composition variables, while sensorial analysis of final wines demonstrated that low and moderate vigour zones produced wines of reserve quality (Johnson et al. 2001). In Tasmania, Australia delineation of a Pinot noir vineyard in four vine vigour zones resulted in wines with clear distinction in phenolic concentration and volatile compounds (Song et al. 2014).

Remote sensing technology with the utilisation of airborne imagery was used to directly predict major grape quality indicators, such as grape phenolics - predominately enclosed in the grape skin (Lamb et al. 2004a). Re-sampling of the image to a final pixel size approximately equal to the row distance (2.5-3 m), and effectively combining vine size and density information into a single pixel, resulted in the strongest correlations to colour and phenols (Lamb et al. 2004a). Strong negative correlations between quality attributes of red grapes (i.e. phenolics and anthocyanins) and canopy NDVI was found to be stronger at the time of veraison, although the relationships established were not strong enough to allow for potential commercialisation at that time (Lamb et al. 2004a). Previous work by Hall (2003) also confirms that analogous airborne imagery of red wine grapes at flowering predicted yield variability (Hall et al. 2003). Ultra-high resolution imagery (0.25 m) separated non-vine and vine pixels (Hall et al. 2003); findings similar to Lamb et al. (2004a) with a resolution of the order of row spacing.

In France, Acevedo-Opazo et al. (2008) conducted a study involving remotely sensed information provided by airborne imagery and soil electrical resistivity on white and red cultivars in non-irrigated vineyards. Temporally consistent relationships (for three growing seasons) between NDVI information and soil electrical resistivity were established and thus, spatial variability of plant water status at the within-vineyard scale was demonstrated. Zones delineated based on the NDVI, indicated differences in vine vegetative growth, yield and vine water status (Acevedo-Opazo et al. 2008). In Ontario, zones were delineated based on soil moisture and leaf ψ (Marciniak et al. 2013). Riesling wines produced from those zones showed unique sensorial attributes and monoterpene concentrations that were highly correlated with vegetation indices (e.g. NDVI) acquired from airborne imagery; low NDVI values were associated with low complexity and low aroma intensity wines.

Precision viticulture was approached at the whole-vineyard scale in northern Spain, on a 90-ha vineyard consisting of 27 blocks planted with more than 65% of the total with *Vitis vinifera* L. cultivar Tempranillo (Santesteban et al. 2013). Vineyard spatial variability with regard to vine vigour was evaluated by measuring the NDVI at the within-field and whole-vineyard scale by multispectral airborne images (30 cm resolution). The study demonstrated that spatial variability in terms of elevation, one barely visible factor at the within-field scale, was showing a general trend of variation at the whole-vineyard scale, which was subsequently affecting the soil water dynamics and soil salinity levels with the lower-lying parts having higher precipitation and salinity levels (Santesteban et al. 2013).

Overall, remote sensing has been proven as a practical implementation for making observations about vineyard vegetative growth and grape composition from multispectral measurements (Reynolds et al. 2010). Yet, remote sensing image acquisition from satellite or airplane platforms requires complicated and time-consuming data processing, such as manual delineation of rows (Puletti et al. 2014), is restricted to weather conditions, and of course involves higher operation costs than the manual data collection (Bramley & Lamb 2003; Stamatiadis et al. 2006). Remotely sensed imagery needs appropriate ground-truthing, such as calibration of the imagery against a measure such as trunk circumference (Bramley et al. 2011b). Most importantly, information may not be available in time to implement critical management decisions (Mazzetto et al. 2010). Sources of imprecision, such as inter-row soil and shadow interference (Stamatiadis et al. 2006) and masking of non-vine pixels (e.g. cover crop) make it difficult to assess vine-specific NDVI (Ledderhof et al. 2015; Reynolds et al. 2010).

1.3.2 PROXIMAL SENSING

Ground-based sensors are the offspring of remote sensing technology, intended to overcome many of the restrictions associated with satellite - or airborne - remote sensing systems (Stamatiadis et al. 2009). As there is an increasing need for the commercial development of a precise on-the-go sensor in order to quantitatively predict fruit quality attributes, continuous measurements are performed on the ground by moving vehicles (Bramley 2010; Matese & Di Gennaro 2015). For this reason, proximal monitoring systems have found wider acceptance, as they offer similar results, easier applicability and higher spatial resolution than remote sensing, while they are associated with lower operating costs.

Proximal sensing technology coupled with remote sensing was used in a Marlborough (New Zealand) Sauvignon Blanc vineyard to demonstrate spatial relationships between trunk perimeter, soil texture and canopy plant cell density (PCD) as an indicator of vine vigour (Bramley 2010). These relationships were further explored by Trought & Bramley (2011) combined with a so called "juice index", developed by surveying winemakers' preferred juice attributes for the "typical Marlborough Sauvignon blanc" at harvest, in order to investigate simultaneously spatial and temporal vineyard variation between veraison and harvest, thereby highlighting the importance of this information to optimising decisions regarding timing of harvest and fruit quality.

As it was previously demonstrated with airborne spectral reflectance imagery predicting pruning weights (Dobrowski et al. 2003), ground-based sensor measurements indicated a consistent association between pruning weight and NDVI over time in Merlot vineyards in northern Greece (Stamatiadis et al. 2006). The ground-based sensors predicted the spatial variation of biomass production near veraison with variable precision; nevertheless, NDVI was nonlinearly correlated with vine size, and was best described by a quadratic regression (Stamatiadis et al. 2006; Stamatiadis et al. 2009). Another study conducted in two vineyards in Northern Greece, planted with Cabernet Sauvignon and Xinomavro (*Vitis vinifera* L.), exhibited that vine productivity in terms of yield was predicted by active canopy reflectance sensors measuring NDVI (Taskos et al. 2013). The sensors had limited effectiveness in predicting berry composition; one of the sensor types was inversely correlated with total phenols showing that dense canopies negatively impact berry colour (Taskos et al. 2013).

1.3.3 ADDITIONAL APPLICATIONS OF PROXIMAL SENSING TECHNOLOGY

Upon delineation of zones, the proximally sensed data can find further applications. For instance, ground-based proximal sensing reflectance sensors were used to identify disease and nutrient (nitrogen) stress symptoms on wheat canopies showing lower NDVI values; clear spectral differences were demonstrated among the control, the pathological and nutritional stressed canopies (Moshou et al. 2006). In grapevines, canopy reflectance measurements identified plant stress as an effect of water shortage and limited fertilizer N uptake (Stamatiadis et al. 2009).

In another study, a mobile monitoring system, consisting of GreenSeeker™ optical sensors and ultrasonic sensors, assessed the canopy health and vigour status of vines in Italian vineyards (Mazzetto et al. 2010, 2011). NDVI maps clearly identified differences in vegetation, whereby low vegetation vigour (low NDVI values) correlated with high incidence of grapevine downy mildew and thus GreenSeeker™ measurements correlated well with the vine phytosanitary status (Mazzetto et al. 2010, 2011).

Since the information acquired from these technologies is the source of primary observations (Bramley et al. 2003), site-specific operations aim to viticultural practices, such as application of fertilisers, irrigation and pruning, according to the real needs of the individual vines instead of a uniform approach. Many commercial solutions for variable rate technology already exist, where real-time information leads to modified vineyard management such as selective harvest, variable-rate leaf stripper, and variable-rate fertilizer spreader (Matese & Di Gennaro 2015).

1.3.4 GREENSEEKER™

GreenSeeker™ (Trimble Navigation Ltd, Sunnyvale, CA) is a multispectral sensor technology which scans the canopies along the rows at high resolution and has an integrated GPS system for data geo-referencing (Matese & Di Gennaro 2015). The sensors are mounted on tractors and they collect real-time high spatial resolution information about canopy health, expressed in vegetation indices, such as the NDVI, while they generate the subsequent NDVI maps in real-time. Among the advantages of this particular system is that it has its own light source and therefore cloud coverage is not an issue.

The first GreenSeeker™ sensors were developed in 1989 and the primary focus was the identification and spray of weeds (Rutto & Arnall 2009). By 1992, scientific discussions involved the potential detection of vine biomass. The first observations by the initial sensors were taken at Oklahoma State University, and NDVI was calculated from the red (660 nm) and near infrared (780 nm) spectral radiance readings. Initially, experiments focused on investigating the extent of spatial variability regarding soil properties and yield in a visibly homogenous area. The introduction of the first GreenSeeker™ sensor occurred in 2002, providing opportunities to the grape growing industry, such as variable-rate application of N fertilizer, pesticides, plant growth regulators, and defoliants based on the crop status and field conditions (Rutto & Arnall 2009).

1.4 CONCLUSION

Clearly, the term terroir encompasses many aspects of vineyard variation within it, all of which are highly interdependent. Extensive research has been conducted to show the spatial variation in vineyards with regard to soil properties, water status, yield components, and berry composition attributes. In order to explore the vineyard variation, many of the recent technological advances have concentrated their focus on the field of precision viticulture. These technologies develop quite quickly, and offer great applicability due to lower costs, ease of use, and versatility. The usefulness of proximal sensing technology, in this case the GreenSeeker™ technology, and its relationship with plant physiological measurements has still to be explored. The resulting outcomes of this research may allow for a wider adoption of Precision Viticulture approach.

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CHAPTER 2 : IMPORTANCE OF WATER RELATIONSHIPS TO SPATIAL VINEYARD VARIABILITY

2.1 ABSTRACT

Water is essential for all living organisms; in grapevines plant physiology, yield, and berry composition are highly influenced by water relationships. Grape vine water status was evaluated by measurement of leaf water potential (ψ) and soil moisture (%). Research was conducted for two vintages (2014 and 2015) on *Vitis vinifera* cvs. Riesling, Cabernet franc and Pinot noir. Results suggest strong inverse relationships among vine water status and grape phenolics, as well as monoterpenes. Leaf ψ was associated with berry size, while yield exhibited strong negative correlations with pH and positive correlations with vine size (in most cases). Principal Component Analysis implemented with *k*-means clustering was considered a satisfactory tool in identifying relationships, since Moran's *I* for soil moisture also indicated strong clustering patterns. Soil moisture and leaf ψ showed only weak correlations with each other. Overall, leaf ψ was a stronger indicator of important berry composition variables (anthocyanins, phenols, colour, and terpenes).

Key words: water relationships, leaf ψ, soil moisture, yield, phenolic concentration, monoterpenes.

2.2 INTRODUCTION

Water is the most limiting abiotic factor to plant growth and productivity (McElrone et al. 2013), and therefore it greatly determines vegetation distributions globally. When leaf stomata open to absorb carbon dioxide (CO_2) from the atmosphere in order to accumulate sugars, water is lost (through transpiration) and when the plants are under water deficit conditions, the stomata close, and the metabolic activity in plants' tissues slows down (Jackson

2008). In grapevines, the assessment of water status is expressed as leaf water potential (ψ), often by using the pressure chamber technique, initially developed by Scholander (Scholander et al. 1965) and later expanded by Turner (1988). Regardless of the method employed, either predawn or midday leaf ψ, it has been widely accepted as an accurate tool for monitoring grape vine water status (Koundouras et al. 2006; Williams & Araujo 2002).

Several researchers have demonstrated that changes in grapevine water status directly impact vine development, growth, vigour, grape composition and wine quality (Hakimi Rezaei & Reynolds 2010; Marciniak et al. 2013; Ojeda et al. 2002; van Leeuwen 2010; van Leeuwen & Seguin 2006). In Agiorgitiko, mean ψ was strongly correlated to vineyard location (soil type), and the low vine water status zones resulted in early ripeness of the berries, limited berry size, sugar, anthocyanins and total phenolics accumulation in berry skins and wines (Koundouras et al. 2006), while similar results were observed in Shiraz (Ojeda et al. 2002) and Merlot (Sivilotti et al. 2005). In Riesling, low water status was associated with increased soluble solids and monoterpenes (Reynolds et al. 2010; Willwerth et al. 2010).

Generally, under water deficit conditions, yield and berry size decreases and total phenolics increase, which leads to lower yields but to higher quality grapes (Koundouras et al. 2006; Sivilotti et al. 2005; van Leeuwen & Seguin 2006; van Leeuwen et al. 2004). On the other hand, high water availability leads to more vegetative growth but reduced sugar, colour and phenol concentrations in the berries (van Leeuwen 2010; van Leeuwen & Seguin 2006). Recently, it was demonstrated that leaf ψ shows considerable variation even at the within-field scale (Acevedo-Opazo et al. 2008a). However, when leaf ψ prediction models were investigated, the driving factors of the variability changed temporally across the season (Taylor et al. 2010).

Within the terroir concept, many factors are incorporated, such as regional climate, canopy microclimate, soil properties and topography, water uptake conditions, viticultural practices and oenological techniques (De Andrés-De Prado et al. 2007; Reynolds et al. 2007; van Leeuwen & Seguin 2006), all of which contribute in shaping vineyard variability. Recently, there has been great focus on the regional character of terroir that confers unique characteristics to the wine, which has a distinctly identifiable origin (Organisation International de la Vigne et du Vin 2010).

Spatial and temporal knowledge acquisition about variability in vineyard water status is currently a major focus in research. When monitoring the vine water status, one should consider not only how the vine water status changes over the growing season (temporally), but also the range of it (spatially) (Acevedo-Opazo et al. 2008b). Since soil is the major substrate for plants, any variability in the water holding capacity, attributable to soil depth and texture, can induce increased variability in plant water status (Acevedo-Opazo et al. 2008b). Thus, soil water content (measured as soil moisture) is found to be highly correlated to leaf ψ and vine size (van Leeuwen & Seguin 2006; Williams & Araujo 2002).

Geospatial technologies including Geographical Information Systems (GIS), remote sensing and Global Positioning Systems (GPS), are reliable information tools (often at high-spatial resolution). When applied in viticulture and in conjunction with other vineyard instrumentation, such as time-domain reflectometry (TDR) for water related measurements, are used to explore the vineyard variability. For instance, identification of different water zones at the vineyard scale is subsequently affecting decision making, such as irrigation schedule design. Much research is focused on the temporal variability of vine water status, targeting the optimisation of irrigation (or deficit irrigation), maximising water use efficiency and enhancement of wine grape quality.

One of the most powerful GIS tools widely used in viticultural research are the spatial interpolation procedures, according to which unknown values can be predicted from a limited number of sample data points at geolocated sites (Bramley 2005). While taking advantage of the new technologies, this study aims to identify the spatial and temporal variability in the vine water status assessment at a within field scale. It was anticipated that spatial patterns of water status would be found in the study blocks. Furthermore, based on varieties and sites, water status relationships were expected to associate with yield and berry composition characteristics, where increased vine water status and soil moisture would relate to higher yield and berry weight, but to lower desirable berry composition characteristics.

2.3 MATERIALS AND METHODS

2.3.1 STUDY PLOT SELECTION

This study focused on three different locations across the Niagara Peninsula, which is situated south of Lake Ontario immediately north of the 43° parallel. Three commercial vineyards in the Niagara Peninsula, Ontario, containing large blocks of *Vitis vinifera* were chosen. Research sites with several grape vine varieties that have the potential and a proven record of heterogeneity for multitude of response variables were selected (Table A 1). Sites were geolocated with the use of advanced Global Positioning System technology (GPS) using an Invicta 115 GPS Receiver (Raven Industries, Sioux Falls, SD) with 1.0 to 1.4 m accuracy and the grape vines were marked in a geolocation grid. Post collection differential correction was conducted using the Port Weller, Ontario base station correction to final accuracy of ≈ 30-50 cm. The coordinates from each study block were imported into spreadsheet software and then visually represented using the GIS program ArcGIS 10.3 [Environmental Systems Research Institute (ESRI), Redlands, CA]. Two study plots were contained in each commercial vineyard, thus the project consisted of six study plots in total (Figure A 1). Measurements were carried out during the 2014 and 2015 growing seasons at the selected commercial vineyards.

i. Cave Spring Cellars

The Cave Spring Cellars vineyard is located on the slopes of Beamsville Bench, Ontario, which is situated in the northwest corner of the Niagara region. In the ≈ 55 ha of Cave Spring vineyards, the main wine grape cultivars grown are Riesling, Chardonnay, Cabernet Franc and Pinot Noir. Two study plots of *Vitis vinifera* cvs. Cabernet franc and Riesling were selected for this vineyard.

ii. Lambert Vineyard

Lambert Vineyard is located in Niagara-on-the-Lake, Ontario and is a 100 ha drip-irrigated vineyard containing several large blocks of *V. vinifera*, including Chardonnay, Riesling, Sauvignon blanc, Merlot, Cabernet Sauvignon, and Cabernet franc. Two study plots of *V. vinifera* cvs. Cabernet franc and Riesling were selected for this vineyard.

iii. Coyote's Run Winery

Coyote's Run Winery is a 23 ha vineyard, located on the St. David's Bench, Ontario. The St. David's Bench along with the Beamsville Bench are positioned on the face of the escarpment, allowing the greatest degree of protection from strong winds in winter. At Coyote's Run winery, wine production mainly involves Pinot noir, Cabernet Sauvignon, Pinot gris and Chardonnay. Two study plots of *V. vinifera* cvs. Pinot noir were selected for this vineyard with the rows oriented in a north-south and east-west direction.

2.3.2 DATA COLLECTION

Data were collected based upon the inherent variability within the blocks, whereby a grid of vines in each block was established and geo-located by GPS. Vineyard study blocks contained approximately ≈85 sentinel vines, of which 20 vines were measured for leaf ψ, bud LT_{50} (=bud hardiness, temperature at which 50% of primary buds die due to artificial freezing), and monoterpene analysis. The sample vines were healthy and representative of the general condition of the vines within the block. Field measurements and grape samples for berry composition analysis were obtained on these vines in all vintages (years 2014 and 2015). Tests were conducted in three different growing season stages: at berry set, lag phase, and veraison. With the exception of harvest and pruning, all regular operations were carried out on the sentinel vines by the vineyard crews.

2.3.3 SOIL MOISTURE

Vineyard soil moisture was measured by time domain reflectometry (TDR) using the Field Scout TDR 300 Soil Moisture Meter (Spectrum Technologies, East Plainfield, IL). The volumetric water content mode (VWC) was used, with the setting modified depending on the clay content of the soil. The volumetric water content in the soil represents the ratio of the volume of water contained in a given volume of soil to the total soil volume. The TDR 300 generates and records the return of high-energy electromagnetic signal that travels down and back through the soil along 20-cm stainless steel probes. Measurements were obtained on all sentinel vines three times during the growing season at berry set, lag phase, and veraison approximately 10 cm from the base of each vine trunk. The mean soil moisture (SM) of each sentinel vine for each one of the periods measured was thereafter calculated from a minimum of two separate readings.

2.3.4 VINE WATER STATUS

Vine water status was measured using midday leaf ψ by the pressure bomb technique (Scholander et al. 1965; Turner 1988). Measurements were conducted only at the designated leaf ψ vines (≈20 per vineyard study plot), on the same days as soil moisture measurements. Observations took place three times over the growing season on days with abundant sunshine. In the case of rain, measurements were delayed for a minimum of 24 hours. Leaf ψ was determined on mature leaves fully exposed to sun, showing no visible sign of damage or disease, between 1000h and 1400h (Turner 1988). Two to three sample leaves from primary shoots were acquired and the time from excision to reading was kept under 5 seconds. After excision, the leaf was quickly introduced into a pressure chamber connected to a pressurised supply of inert gas (nitrogen) [Model 3015G4 Plant Water Status Console (Soil Moisture, Santa Barbara, CA)], and pressure was increased at a steady rate. When equilibrium between the chamber and atmospheric pressure was reached, sap started to flow from the leaf petiole. The pressure reading at that point was recorded in negative bar units (10 bars = 1 MPa). If two measurements were more than 0.15 MPa apart (approximately 15% of the reading), then a third leaf was sampled.

2.3.5 YIELD COMPONENTS AND VINE SIZE

Harvest dates for each research block were at the discretion of vineyard managers. At all sites, sample collection from all sentinel vines took place as close to commercial harvest as possible. Each sample vine was individually hand-harvested in order to determine cluster number and yield (kg) using a portable field scale. Mean cluster weight (kg) was also calculated from these data. Samples of 100 berries were randomly collected from clusters of each sentinel vine, transferred to the lab and were stored at - 25°C until time of analysis; additional samples from the smaller subset of Riesling sentinel vines were kept for monoterpene analysis.

In winter 2014 and 2015, the sample vines were hand pruned during the dormant season. Cane prunings were retained and immediately weighed on-site using a digital field-portable scale to determine vine size (kg) in all vineyard blocks. Bud hardiness was evaluated using the Differential Thermal Analysis (DTA) method; an incision was made across the dormant sample bud, which was slowly frozen by a programmable freezer. The temperature at which 50% of the buds were dead was recorded.

2.3.6 BERRY COMPOSITION ANALYSIS

Berry samples were removed from - 25°C storage, weighed to determine mean berry weight and placed into 250-mL beakers. The berry samples were heated at 80°C in a water bath (Isotemp 228, Fisher Scientific, Mississauga, ON) for one hour to dissolve precipitated tartrates and to facilitate extraction of anthocyanins from the skins. Berry samples were homogenized in a commercial juicer (Omega 500™, Denver, CO). The settled juice was centrifuged at 1298 *g* for 10 min [IEC Centra 91 CL2 (International Equipment Company, Needham Heights, MA)] in order to remove any debris. The clear juice was used for subsequent berry composition analysis.

i. Soluble solids, pH, titratable acidity

Analysis of berry pH was conducted by an AR50 pH meter with a standardized VWR Symphony electrode (Model AR93312527, Fisher Scientific, Mississauga, ON). Soluble solids (°Brix) were measured using an Abbé refractometer (Model 10450; American Optical, Buffalo, NY). An automatic PC-Titrate autotitrator was used to determine titratable acidity (TA) (Model PC1300-475, Man-Tech Associates Inc., Guelph, ON) to an endpoint of pH 8.2 using 0.1N sodium hydroxide (NaOH). Prior to sample measurement, three water samples and three standard solutions of tartaric acid were run to condition and calibrate the machine. Approximately 20 mL of juice was retained at - 25°C for subsequent analysis of total anthocyanins and phenols for the red cultivars.

ii. *Monoterpene analysis*

Determination of monoterpene concentration in Riesling berries was based on the method developed by Dimitriadis and Williams (1984), as modified by Reynolds and Wardle (1989). Frozen berry samples (100 g) were allowed to thaw at room temperature and immediately before distillation the sample was homogenized and pH was adjusted to 6.7 using 20% NaOH. Samples were steam-distilled to allow collection of the first fraction of 25 mL free volatile terpenes (FVT) distillate within 15 min, and then acidification with 10 mL of 50% H_3PO_4 followed, after which 40 mL of PVT distillate were collected in 20 min. The free volatile terpene (FVT) and potentially-volatile terpene (PVT) concentrations were expressed in mg/L.

iii. *Total anthocyanins, colour, total phenolics*

Total anthocyanins in berries were quantified using the pH shift method by Fuleki & Francis (1968). Two buffer solutions were prepared; pH 1.0 buffer was prepared with 0.2 M KCl with 0.2M HCl, and pH 4.5 buffer with 1M sodium acetate with 1M HCl in distilled water (Vankar & Srivastava 2010). One mL of each juice sample was diluted with 9mL of both buffers, allowed to equilibrate in the dark for 1 h and then the absorbance was measured at 520 nm wavelength against a blank (the appropriate buffer solution) using an Ultrospec 2100 pro

UV/Vis spectrophotometer (Biochrom Ltd., Cambridge, UK). The total anthocyanin concentration was calculated using the following formula:

$$\text{Total anthocyanins (mg/L)} = A_{520}\ (\text{pH } 1.0 - \text{pH } 4.5) \times 255.75.$$

Color intensity was demonstrated according to a modified method provided by Mazza et al. (1999). Absorbance values were measured at 520nm on an Ultrospec 2100 Pro UV/Vis spectrophotometer (Biochrom Ltd., Cambridge, UK). The blank used was a pH 3.5 buffer (0.1M citric acid and 0.2M Na_2HPO_4). In the case that the samples were too dark to measure, they were diluted 1:10 (in 9 mL of pH 3.5 buffer), mixed, equilibrated for 1 h in the dark, and poured into a 10-mm plastic cuvette.

Total phenols were measured on all prepared samples using the Folin-Ciocalteu micro method (Waterhouse 2006) based on Singleton & Rossi (1965). A 1 mL centrifuged juice sample was diluted with 9 mL distilled water; 20 µL from this mix were pipetted into cuvettes followed by 1.58 mL of water plus 100 µL of 2N Folin-Ciocalteu reagent (Sigma- Aldrich, F9252). The sample was mixed well and allowed to heat for 8 min. Next, 300 µL of sodium carbonate ($NaCO_3$) solution (200 g/L) were added, and again mixed well and kept in the dark at 20°C for 2 h. The absorbance was measured at 765 nm and concentration was expressed as mg/L gallic acid equivalents (GAE) by plotting the values on a standard curve.

2.3.7 STATISTICAL ANALYSIS

Data analysis was performed on all variables using XLStat-Pro statistical software (2015 version, Addinsoft, New York, NY). Initially, all variables were checked for normality and errors, since normal distribution of the observations in the dataset is assumed for parametric tests, such as Pearson *r* (Warner 2008). For all statistical tests, the level of significance (α-level) was set at 95%. Using univariate parametric statistics all data points were carefully inspected to identify any extreme outliers, while the primary focus was to maintain the integrity of the data. Only after detailed analysis of histograms, bivariate scatter graphs and box plots, outlier observations were not included since they can have a disproportionate impact on the value of Pearson *r* (Warner 2008).

Subsequent to checking all data for normality and errors, Pearson correlation tests were performed to examine the strength of linear relationships among the variables and to provide the basis for further multivariate analysis (Warner 2008). In PCA for instance, even a minor sampling error can potentially change the actual eigenvector in the correlation matrix (de Winter & Dodou 2016). Therefore, highly correlated variables (p-value < 0.0001) were removed in order to avoid cases of multi-colinearity, which can influence unreliably and inaccurately regression coefficients (Warner 2008). The variable "cluster weight" derives from other variables (yield/cluster number), and was found highly correlated in all vineyard sites. Thus, it was omitted from further analysis, as it might have compromised it by over-emphasizing particular eigenvectors (directions) and under-representing substantial remaining relationships. Similarly, for the variables "Soil Moisture", "LT_{50}" and "Leaf Water Potential" only the means were retained for further analysis. Linear regressions were also created to visually display relationships among variables, where the dependent variables (here soil moisture and leaf ψ) are essentially a linear function of one or more independent variables (Yao et al. 2013).

Principal component analysis (PCA) is a very useful multivariate technique to analyse a data set consisting of several inter-correlated quantitative dependent variables, when trying to reduce the dimensionality of a large number of variables (Bersimis et al. 2007). PCA is frequently preferred over other factor statistical analysis methods in several research fields due to its simplicity in computation and interpretation (de Winter & Dodou 2016), and it was used here to illustrate relationships among the grapevine-related variables. Principal Components are the linear orthogonal combinations of the original variables with the first component accounting for the largest possible variance in the dataset, while the ultimate aim is to "extract" the largest possible amount of variance with the minimum number of components (Abdi & Williams 2010; de Winter & Dodou 2016).

When the variables have short eigenvectors (appear to be close to the center of the PCA circle), some of the information is carried on other axes/components and therefore, any interpretation is uncertain. Hence, the squared cosines of the variables were examined in detail here, as they indicate the representation quality, and importance of a variable on the PCA axis; the larger the value of $\cos^2$ the more it contributes to the total distance of the observation to the origin (Abdi & Williams 2010). In our analysis, the option to resize all plotted points based on $\cos^2$ values was selected, in order to confirm whether the variables were well linked to the axes.

Among the cluster analysis techniques, *k*-means is the most important non-hierarchical classification algorithm where multidimensional data are classified into *k* classes (clusters). The class centroid has the minimum Euclidean distance from each data point within the cluster (Tagarakis et al. 2013). This method has been previously used in viticulture to delineate zones (Arno et al. 2011; Bramley 2005; Bramley & Hamilton 2004; Tagarakis et al. 2013) and for the purpose of this thesis, three clusters of low, medium and high soil moisture were chosen and visually projected on the PCA observation biplot as a qualitative variable.

2.3.8 MAPPING PROCEDURES

Sentinel vines were geo-located, which is defined as the process of obtaining spatial information for the individual vines, mainly about the geographical location (latitude and longitude) (Jollineau & Fast 2013; Matese & Di Gennaro 2015). The Global Positioning System (GPS) technology, is a satellite-based navigation system, which provides rapid, precise and highly accurate, three dimensional (3D) information (Matese & Di Gennaro 2015). For all mapping procedures the GIS software package ArcGIS 10.3 (Environmental Systems Research Institute (ESRI) Redlands, CA) was used. All data was stored in Microsoft Excel spreadsheets. The tool "Create Feature Class from XY Table" was used to import it into ArcMap 10.3, where the sentinel vines with the detailed geographical information were plotted as individual points on the map. All field-based measurements along with chemical analysis variables were thereafter attributed to the geo-referenced dataset and map layers were produced for all variables, cultivars, sites, and vintages.

Spatial interpolation methods provide powerful spatial data analysis tools for estimating values of a variable of environmental importance at unsampled locations using information from point data measurements. Kriging and inverse distance weighting (IDW) spatial interpolation techniques are the most commonly compared and applied methods in environmental sciences (Gong et al. 2014; Li & Heap 2011). More specifically, inverse distance weighting or inverse distance weighted (IDW) method uses a "linear combination of values at sampled points weighted by an inverse function of the distance from the point of interest to the sampled points" in order to predict the values of an attribute at un-sampled points (Li & Heap 2008). Compared with kriging, IDW is appraised as a generally simpler interpolation method, often superior, and more accurate, as uniform distribution of the values is not a prerequisite, a condition that cannot be met in natural situations (Gong et al. 2014).

The theory behind IDW is that the interpolated points are more influenced by points closer to them rather than the more distant ones (Shahbeik et al. 2014). The value of the power parameter (the significance of the closest neighbouring samples on the interpolated values) is the primary influence on the precision of the method (Li & Heap 2008; Yao et al. 2013). The interpolating surface is a weighted average of the scatter points, usually proportional to the inverse of the squared distance of observed and predicted points. The weight of each data point decreases as the distance increases, particularly as the value of the power parameter increases, thus neighbouring observations have a heavier weight and greater influence on the prediction (Li & Heap 2008; Shahbeik et al. 2014).

In this study, the Geostatistical Analyst tool within ArcGIS was utilised, to create a continuous surface (raster) of vineyard study blocks from all point-data variables. The IDW interpolation method postulates that the projected pattern is driven by local variation and does not presume any statistical properties in the original dataset. Thus, IDW was considered appropriate for the purpose of our analysis. The geometry of the neighborhood, or the surrounding points affecting the output, was set at four sectors shifted (45°) and the power value, or the degree of influence of the distant points on the interpolated values was set at optimised. All variables (i.e. soil moisture, leaf ψ, yield components, and berry composition characteristics) were mapped in the North American Datum NAD83, which is a geographic reference system suitable for use in North America - between 84°W and 78°W, and projected in the Universal Transverse Mercator zone 17N. Lastly, the observations were divided into classes based on natural breaks - a classification method that takes all the values being mapped and selects class breaks based on natural clustering in the data; points on the maps represent single (sample) vines.

2.4 RESULTS

Vine water status measurements (leaf ψ and soil moisture) were analysed with yield components, berry composition, and bud hardiness data. Summarised statistics for all variables along with probability (*p*-value) tables are provided for all sites and all vintages in the Appendix (Tables A3-A9 and A10-A21 respectively). In those cases that significant relationships among soil moisture or leaf ψ were identified, scatter plots were created. The 2015 LT_{50} results did not show any significant correlations with soil moisture and leaf ψ; therefore, they were not included in the subsequent data analysis. PCA was conducted for the means of soil moisture, leaf ψ, and LT_{50}. Observation biplots are displayed in different colours based on low, medium and high soil moisture levels, as a result of *k*-means clustering projection.

2.4.1 PEARSON'S CORRELATION RESULTS

Pearson's correlation tables for soil moisture and leaf ψ, along with significance levels can be found in Tables 2.1-2.2.

i. Soil moisture and leaf ψ vs. yield components

Soil moisture correlated with berry weight in Cave Spring Cabernet franc 2014 (positively; Figure 2.1) and in Pinot noir East West 2014 (negatively; Figure 2.2) and was positively related to cluster number and yield in Pinot noir North South block 2015 (Figure 2.3). Soil moisture was negatively correlated with cluster number and yield at Cave Spring Riesling 2014 (Figure 2.4) and with cluster weight at Lambert Riesling 2015. Leaf ψ was positively correlated with berry weight in Pinot noir East West (both years; Figures 2.5-2.6) and North

South 2015 block (Figure 2.7) along with the cluster weight, while it was negatively correlated with cluster number in Cave Spring Cabernet franc 2014 (Figure 2.8) and yield in Cave Spring Cabernet franc 2015 (Figure 2.9). Leaf ψ at Cave Spring Riesling 2014 (Figure 2.10) was positively correlated with berry weight.

January LT_{50} was positively associated with leaf ψ in Lambert Cabernet franc 2014 (Figure 2.11) and Pinot noir North South 2014. February LT_{50} was positively associated with leaf ψ in Pinot noir North South 2014, with SM in Cave Spring Cabernet franc 2014 (Figure 2.1) and Pinot noir North South 2015 (negatively). Mean bud hardiness LT_{50} was positively associated with leaf ψ in Lambert Cabernet franc 2014 (Figure 2.11) and Pinot noir North South 2014 (Figure 2.12), while it was strongly positively associated with SM in Lambert Riesling 2015.

ii. Soil moisture and leaf ψ vs. berry composition characteristics

Soil moisture was negatively correlated with Brix in Cave Spring Cabernet franc 2014 (Figure 2.1), with pH in Pinot noir East West (both years; Figures 2.2, 2.13) and Pinot noir North South 2015 (Figure 2.3), and with TA in Pinot noir North South 2015 (Figure 2.3) and Lambert Riesling 2015 (Figure 2.14). Cave Spring Cabernet franc 2014 (Figure 2.1) showed positive correlations among TA and SM. Leaf ψ was negatively correlated with Brix in Lambert Riesling 2014 (Figure 2.15), Pinot noir East West 2015 (Figure 2.6) and North South 2015 (Figure 2.7), positively with pH in Pinot noir North South 2015 (Figure 2.7) and positively with TA in Pinot noir North South 2014 (Figure 2.12) and Lambert Riesling (both years; Figures 2.15-2.16).

iii. Soil moisture and leaf ψ vs. secondary metabolites

Soil moisture was negatively correlated with anthocyanins in Lambert Cabernet franc (both years; Figures 2.17-2.18), Cave Spring Cabernet franc 2014 (Figure 2.1), Pinot noir East

West 2014 (Figure 2.2) and Pinot noir North South 2014 (Figure 2.19) and with colour in Cave Spring Cabernet franc 2014 (Figure 2.1) and Pinot noir East West 2014 (Figure 2.2).

Leaf ψ was negatively correlated with anthocyanins in Pinot noir North South 2014 (Figure 2.12) and East West 2015 (Figure 2.6), with colour in Pinot noir North South (both years; Figures 2.7, 2.12), and with phenols in Pinot noir East West 2015 (Figure 2.6). However, it was positively correlated with anthocyanins and colour in Pinot noir East West 2014 (Figure 2.5) and with phenols in Cave Spring Cabernet franc 2014 (Figure 2.8) and Lambert Cabernet franc 2015 (Figure 2.20). Soil moisture was positively correlated with FVT and PVT in Lambert Riesling 2015 (Figure 2.14), while leaf ψ was negatively correlated with FVT in Lambert Riesling 2015 (Figure 2.16) and with PVT in all four Riesling blocks (e.g., Figure 2.21).

In summary, soil moisture revealed inconsistent relationships over the 2 yrs of study; secondary metabolites in the red varieties, such as anthocyanins and colour were negatively correlated with soil moisture (five and two of eight blocks, respectively) (Table 2.2). In some cases, such as in Lambert Cabernet franc 2014, Pinot noir East-West block 2014 and North-South block 2014, all three soil moisture measurements in the growing were consistently negatively correlated to anthocyanin concentrations, while specifically in Lambert Cabernet franc 2015 soil moisture in September was negatively correlated with anthocyanins, colour and phenols ($p=0.013$, 0.003, and 0.002 respectively). Similarly, leaf ψ demonstrated strong negative relationships only with PVT (all four Riesling blocks across both seasons) and sparse correlations with the other variables (Table 2.1). Lastly, yield displayed strong negative correlations with pH (12 of 12 blocks), positive with vine size, berry weight and vine water status measurements (six, four, four of 12 blocks, respectively) and negative with just phenols and colour (two of eight blocks).

2.4.2 PRINCIPAL COMPONENT ANALYSIS RESULTS

i. *Cabernet franc*

Principal components analysis (PCA) for Lambert Cabernet franc 2014 explained 36.18% of the total variability of the dataset in the first two principal components (PCs). Anthocyanins and colour were strongly negatively related to soil moisture, leaf ψ was positively related to vine size and LT_{50}, and yield was strongly negatively correlated to pH (Figure 2.22a). Results of *k*-means are showing clustering of low soil moisture observations closely to important berry composition variables, such as anthocyanins, colour, and phenols (Figure 2.23a). In 2015, PC1 and 2 accounted for 43.29% of the variability, with soil moisture similarly to 2014 negatively correlated with anthocyanins, colour, and phenols, while yield and cluster number were strongly negatively correlated to pH (Figure 2.22b). Clusters of low soil moisture were associated with berry composition characteristics, whereas clusters of high soil moisture were grouped closer to yield components (Figure 2.23b).

PCA for Cave Spring Cabernet franc 2014 accounted for 46.71% of the total variability of the dataset in the first two PCs. In the first PC, berry weight, TA, vine size, and soil moisture were negatively correlated with pH, Brix, anthocyanins, colour, and phenols, while PC2 showed negative correlations among leaf ψ and yield (Figure 2.24a). *K*-means clustering results showed high soil moisture observations grouped closely to yield components, whereas low and medium observations were located closer to berry composition variables (Figure 2.25a). In 2015, PCA explained 39.56% of the variability in the first two PCs, and revealed few significant relationships; Brix, anthocyanins, colour, and phenols were closely positively related as well as soil moisture with leaf ψ (Figure 2.24b). *K*-means clustering did not indicate clustering of the observations to the variables examined.

ii. Pinot noir

PCA for Pinot noir East-West 2014 explained 40.17% of the variability in the dataset in the first two PCs, with soil moisture conferring strong negative correlations with anthocyanins, berry weight, yield and cluster number in PC1, while Brix was related negatively to colour (Figure 2.26a). Low soil moisture clusters were found closely located with berry composition variables (colour and anthocyanins) (Figure 2.27a). In East-West 2015, leaf ψ and berry weight were negatively correlated with Brix, anthocyanins and phenols, while yield, cluster number and pH were inversely associated with TA (Figure 2.26b). Subjection of the observations to *k*-means clustering did not reveal any patterns in the dataset.

PCA for Pinot noir North-South 2014 accounted for 38.36% of the variability in the first two PCs; soil moisture and leaf ψ were negatively correlated with anthocyanins and colour (in PC1), while cluster number and yield were inversely correlated with berry weight and pH (Figure 2.28a). Observations with low soil moisture levels occurred closer to berry composition characteristics (Brix, phenols, anthocyanins, and colour), whereas higher levels of soil moisture coincided with yield related variables (Figure 2.29a). In 2015, PCA explained 41.28% of the variability in the first two PCs; soil moisture was associated with yield and cluster number (positively) and with pH (negatively), while leaf ψ was inversely correlated with anthocyanins and colour (Figure 2.28b). *K*-means clustering did not reveal any particular grouping in the dataset (Figure 2.29b).

iii. Riesling

In Cave Spring Riesling 2014, PCA accounted for 37.40% of the variability; soil moisture and pH were inversely correlated with cluster number, yield and vine size in PC1, while berry weight and leaf ψ were negatively correlated with PVT in PC2 (Figure 2.30a). There was some indication of higher soil moisture levels clustering towards soil moisture and berry weight, and the opposite is observed for terpenes (Figure 2.31a). In 2015, PCA explained 37.06% of the variability in the first two PCs; cluster number, yield, and TA were inversely correlated with pH, while leaf ψ and soil moisture were very closely associated. Berry weight was inversely correlated with FVT and PVT (Figure 2.30b). Low soil moisture level observations were found to be clustered closer to FVT and PVT (Figure 2.31b).

PCA for Lambert Riesling 2014 accounted for 51.80% of the variability in the first two PCs and the majority of the variables were represented in the first two PCs (except for soil moisture). More specifically, cluster number, yield and TA were inversely correlated with Brix, pH and berry weight, while leaf ψ was inversely correlated with FVT and PVT (Figure 2.32a). Furthermore, *k*-means clustering revealed grouping of the higher soil moisture in PC1, whereas lower water status observations were found closer to the terpenes (Figure 2.33a). In 2015, PCA explained 48.16% of the variability in the dataset in the first two PCs; leaf ψ and TA were inversely correlated with pH, FVT, and PVT (PC1), while soil moisture was closely associated to yield and cluster number (PC2) (Figure 2.32b). High soil moisture was associated with both FVT and PVT in *k*-means clustering (Figure 2.33b).

In summary, PCA demonstrated that soil moisture was highly negatively correlated with berry composition characteristics in Cabernet franc and Pinot noir blocks for anthocyanins, colour and phenols (six, four, three of eight blocks, respectively), while yield was negatively correlated with pH (seven of 12 blocks). Lastly, leaf ψ was inversely correlated with anthocyanins, colour and phenols for red wine grapes (three, one, and two of eight blocks respectively), and with FVT and PVT for Riesling (one and three of four blocks, respectively).

In general, PCA was in agreement with Pearson's correlations and indicative of strong relationships among the variables reported here. When both Pearson's correlations and PCAs were compared, low soil moisture was associated with higher anthocyanins, phenols and colour, while *k*-means clustering confirmed the latter (five out of eight blocks). Similar patterns were demonstrated for leaf ψ and phenolics (PCA results only), along with terpenes, while *k*-means clustering verified the patterns (three of four blocks). Low yield resulted in low berry weight and water status (four of twelve blocks), but higher pH. Soil moisture showed inconsistent patterns over the two growing seasons, whereas leaf ψ was a stronger identifier of important berry composition variables (anthocyanins, phenols, colour, and terpenes). Soil moisture and leaf ψ showed weak correlations with each other.

2.4.3 MORAN'S *I* INDEX

Moran's Index (Moran's *I*) is regarded as the most common global measure of spatial autocorrelation; it is based on the concept that observations closer to each other are more similar than distant ones and values vary on a scale between –1 through 0 to +1. Moran's *I* tables can be found in the Appendix (Tables A22-A27) for all vineyard sites and vintages. When comparing all variables, including yield components and berry composition, Moran's *I* results lend weight to the view that there is strong clustering for the variable soil moisture (clustering incidence >90% in four of six blocks for both years, Cave Spring excluded). On the contrary, leaf ψ showed sparse clustering patterns; the mean clustering incidence was only 25% for all sites and thus it was not considered a strong indicator of spatial autocorrelation. Moran's *I* for variables related to yield (i.e. cluster number, yield, cluster weight, berry weight) indicated no spatial autocorrelation (>80% was random in all six blocks for both vintages); vine size was also found random in most cases (nine of eleven). Berry composition variables for Cabernet franc and Pinot noir showed a random pattern (>75% in the four blocks for both years). Although the same was noted for basic berry composition variables in Riesling (Brix, pH, TA) (>80% randomness both blocks in both years), the terpenes clearly demonstrated a clustered pattern (87.5% clustering incidence).

2.5 DISCUSSION

Initially, it was hypothesized that the vine water status assessment at the within field scale would reveal spatial patterns of water status relationships with yield and vine size. Results presented in this chapter were partially in line with the hypothesis. Generally, vine water status (both leaf ψ and soil moisture) exhibited relationships with yield components, but not with vine vigour. Indeed, higher leaf ψ (and thus lower water stress in the vines) was directly related to higher berry size, yet without directly promoting higher yields in all cases. Research suggests that under water deficit conditions yield and berry size decreases (Santesteban & Royo 2006; Sivilotti et al. 2005; van Leeuwen & Seguin 2006), but other authors did not find an influence of vine water status on yield and berry weight (Koundouras et al. 2006). Relationships among soil moisture and yield components were hardly identifiable and often negative in nature. Those negative relationships may be attributed to high temperatures observed in the Niagara Region (Tables A2-A3) inducing high transpiration rates leading to unbalanced vines due to vegetative growth; another interpretation being a "stress memory" from previous seasons, which resulted in decreased water uptake (Koundouras et al. 2006; Sivilotti et al. 2005). Moderate water deficit is attributed to hot and dry climates (high ETc and/ or low precipitation), to low soil water holding capacity (gravelly soil) and depth, along with accessibility to the water table (Koundouras et al. 2006; Seguin 1986; van Leeuwen et al. 2004; van Leeuwen & Seguin 2006). Lastly, only in some cases (50%) higher yield correlated with higher vine vigour, in agreement with previous work conducted in the region where inconsistent relationships were revealed for vine size (Ledderhof et al. 2014; Reynolds et al. 2007), possibly attributable to vineyard management practices, such as hedging and basal leaf removal.

The climate in the Niagara Region is a humid continental climate, with precipitation spread throughout the year (Shaw 2005). The 7-month growing season total precipitation recorded by the weather stations in the region ranged from 500 mm to 648 mm (Figure A 2). Moisture is often unequally dispersed over the region during the warm months of July and August, which results in the upper soil layer turning droughty due to high evapotranspiration rates and low precipitation, thus inducing vine water stress (Shaw 2005; Sivilotti et al. 2005). Leaf ψ measurements were obtained close to solar noon, when the evaporative demand by the atmosphere is the highest. Yet stomatal behaviour (and therefore transpiration rate) varies among plants and that makes the values of leaf ψ quite variable between leaves and plants (Acevedo-Opazo et al. 2008b, 2010a). Correlations presented here might have been improved by the use of pre-dawn leaf ψ or stem ψ. Pre-dawn leaf ψ is widely used, since the grapevine is considered to be in equilibrium with soil conditions at that time, and thus the soil effect is more strongly reflected in the measurements (Acevedo-Opazo et al. 2013; Santesteban & Royo 2006; Sivilotti et al. 2005; Song et al. 2014; Taylor et al. 2010; Tramontini et al. 2013; van Leeuwen et al. 2004).

Furthermore, issues with soil moisture may be attributed to soil type, landscape roughness and root depth; some authors consider soil moisture monitoring an impractical and expensive methodology for irrigation scheduling in areas with high root depth (Acevedo-Opazo et al. 2010a; Sadikhani 2014). Our existing instrumentation (TDR probes) can only reach a depth of 20 cm; water available to the vines might have been deeper in the soil and thus soil water content may not be precisely depicted here. While rooting penetration depth varies widely and most of the absorption occurs on the top 60 cm of the soil, roots can potentially reach a depth of more than 6 m (Jackson 2008). In addition, direct measurements close to the root zone are complex, as the heterogeneity of soils can restrict oxygen, water, and nutrients availability to the roots. Generally, soils with higher clay content are associated with stronger soil-water retention and decreased root development, with subsequent implications to vigour and yield components due to water uptake restrictions (Fraga et al. 2014; van Leeuwen & Seguin 2006). Thus, the presence of water did not essentially translate to water accesible to the vines. Indeed, the soil moisture was generally higher in soils with higher clay content, and as such at Coyote's Run, but without the vines actually being able to access it (Reynolds 2010).

It was hypothesized that vine water status measurements would also relate to berry composition characteristics. This hypothesis was fully confirmed by the results presented in this chapter. More specifically, low soil moisture was associated with higher phenolics in red cultivars and low leaf ψ with high monoterpene concentrations in Riesling. It is well established in the literature that low vine water status has a positive impact on grape phenolics, an effect particularly pronounced in anthocyanins (Table 2.2) (Acevedo-Opazo et al. 2010b; De Andrés-De Prado et al. 2007; Intrigliolo et al. 2012; Ojeda et al. 2002; Seguin 1986; van Leeuwen 2010; van Leeuwen et al. 2004). A general pattern of smaller berries with higher phenolics was noted as in Bramley (2001), but it was not consistent throughout the years; the elevated anthocyanin concentration is not merely attributable to smaller berry size, but also to improved cluster microclimate or to beneficial accumulation conditions (Koundouras et al. 2006). Higher phenolics were usually associated with higher Brix, in agreement with literature (Acevedo-

Opazo et al. 2010b; Koundouras et al. 2006; Song et al. 2014), yet pH and titratable acidity showed no particular correlation with vine water status, as other authors have also demonstrated (Acevedo-Opazo et al. 2010b; Sivilotti et al. 2005). Although yield did not show any significant influence on berry composition quality attributes here, as in van Leeuwen (2004) it was consistently inversely correlated with pH in all six vineyard blocks over two seasons.

In Riesling, both correlation tests and PCAs strongly confirmed an inverse relationship among leaf ψ and terpenes, more so PVT than FVT, as in other studies (Reynolds et al. 1996a,b; 2005). Sunlight exposure has been demonstrated to be a major factor affecting high concentration of monoterpenes, when different training systems in Riesling (Reynolds et al. 1996b), or basal leaf removal in Gewürztraminer were investigated (Reynolds et al. 1996a). Temperature has also been demonstrated as an important factor affecting monoterpene concentration; cooler temperatures during ripening predominantly result in higher FVTs (Skinkis et al. 2010). However, in this work, warmer temperatures (in 2015; Tables A2-A3) did not decrease the monoterpenes due to volatilization or degradation as in Skinkis et al. (2010), but increased them instead in agreement with other authors (Belancic et al. 1997; Reynolds et al. 1996a). Moreover, it has been demonstrated that low vine vigour associates with higher terpenes concentrations by allowing sun exposure (Reynolds et al. 2007; Skinkis et al. 2010), a relationship only slightly verifiable in the results presented here, and in disagreement with (Marciniak et al. 2013). Aside from an inverse relationship with pH, yield components did not show any significant influence on berry composition characteristics.

Regression scatter plots were produced to explore the nature of relationships among soil moisture or leaf ψ and the response variables (i.e. yield components and berry composition). Significant relationships reported here were sufficient in determining the associations among the investigated variables, regardless of the relatively low R^2 value, since regressions were not used for predicting the response variables. PCA was determined to be a satisfactory technique to explore the interrelations among vine water status and other variables, widely adopted by researchers (Acevedo-Opazo et al. 2010b; Cortell et al. 2008; Ledderhof et al. 2015; Marciniak et al. 2013; Song et al. 2014). Although PCA accounted for a relatively low percentage of the variability in the dataset (≈40%), the relationships found here were generally consistent and in agreement with literature. In conjunction with PCA, *k*-means clustering analysis for the soil moisture variable revealed underlying structures associated with important berry composition variables (i.e. phenolics and terpenes), decision which was further supported by the Moran's *I* results suggesting strong clustering patterns for soil moisture measurements throughout the season. Moran's *I* is the most commonly used index to indicate spatial autocorrelation (i.e. clustering in the dataset), however it is not capable of distinguishing high/low spots among the observations. On the contrary, *k*-means clustering can highlight clustering patterns in the data and allocate the observations accordingly; much research has exploited this technique, predominantly its spatial applicability (Arno et al. 2011; Bramley 2005; Bramley & Hamilton 2004; Bramley et al. 2011; Scarlett et al. 2014; Tagarakis et al. 2013).

2.6 CONCLUSIONS

The principal hypotheses were the expectation of relationships among vine water status and yield components, as well as berry composition variables. It was anticipated that soil moisture, leaf ψ, berry weight and vine size would inversely relate to Brix, phenolics and monoterpenes. The results confirm the hypotheses, and are in good agreement with current literature. Overall, vine water status related to yield components, with low leaf ψ directly associated with berry size but not with yield in all cases, while yield was consistently inversely correlated with pH. Smaller berries exhibited higher phenolic concentrations and Brix in Cabernet franc and Pinot noir. In Riesling, an inverse relationship among leaf ψ and terpenes, predominantly in PVT was revealed. Soil moisture and vine size showed inconsistent correlations with instrumentation utilised here (TDR only reaches a 20 cm depth - water available to the vines might not be accurately measured), and vineyard operations (such as certain canopy management practices, including hedging and basal leaf removal) may have been plausible reasons.

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2.8 TABLES AND FIGURES

2.8.1 PEARSON'S CORRELATIONS

Table 2.1 Pearson's correlation coefficients for soil moisture (%) and leaf water potential (MPa) for the Riesling blocks in 2014 and 2015.
Only variables with significant relationships were included, and empty cells represent no relationship. Significance levels are indicated as follows: p<0.05 bold, p<0.01 bold and underlined, and p<0.001 bold and double underlined.

SOIL MOISTURE (%)											
VINEYARD SITE	VARIETY & YEAR	NDVI July	Mean NDVI	Cluster number	Yield (kg/vine)	Titratable Acidity (g/L)	Free Volatile Terpenes (mg/L)	Potentially Volatile Terpenes (mg/L)	Mean Bud LT_{50}	Leaf Water Potential July (MPa)	Cluster weight (kg)
Lambert	Riesling 2014										
	Riesling 2015	-0.635	-0.385			-0.250	0.430	0.533	0.850	-0.242	-0.239
Cave Spring	Riesling 2014			-0.348	-0.321						
	Riesling 2015										

LEAF WATER POTENTIAL (MPa)										
VINEYARD SITE	VARIETY & YEAR	NDVI July	NDVI August	Mean NDVI	Berry weight (g)	Soluble Solids (°Brix)	Titratable Acidity (g/L)	Free Volatile Terpenes (mg/L)	Potentially Volatile Terpenes (mg/L)	Soil Moisture July (%)
Lambert	Riesling 2014	-0.240	-0.316	-0.276		-0.359	0.334		-0.333	0.242
	Riesling 2015						0.332	-0.247	-0.298	
Cave Spring	Riesling 2014				0.305				-0.474	
	Riesling 2015								-0.228	

Table 2.2 Pearson's correlation coefficients for leaf water potential (MPa) and soil moisture (%) for the Cabernet franc and Pinot noir blocks in 2014 and 2015. Only variables with significant relationships were included, and empty cells represent no relationship. Significance levels are indicated as follows: $p<0.05$ bold, $p<0.01$ bold and underlined, and $p<0.001$ bold and double underlined.

LEAF WATER POTENTIAL (MPa)

VINEYARD SITE	VARIETY & YEAR	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocyanins (mg/L)	Colour (au)	Phenols (mg/L)	January Bud LT_{50}	February Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Mean Soil Moisture (%)
Lambert	Cabernet franc 2014													0.354		0.274	-0.233		
	Cabernet franc 2015												0.337						
Cave Spring	Cabernet franc 2014					-0.238							0.326						
	Cabernet franc 2015		-0.255		-0.249														
Coyote's Run	Pinot noir EW 2014						0.273				0.337	0.218						-0.265	-0.249
	Pinot noir EW 2015			0.279	0.261		0.301	-0.247			-0.270		-0.341						
	Pinot noir NS 2014									0.297	-0.280	-0.208		0.412	0.259	0.423			
	Pinot noir NS 2015	0.223					0.211	-0.262	0.246			-0.322							

SOIL MOISTURE (%)

VINEYARD SITE	VARIETY & YEAR	NDVI July	NDVI August	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocyanins (mg/L)	Colour (au)	February Bud LT_{50}	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Mean Leaf Water Potential (MPa)
Lambert	Cabernet franc 2014										-0.345				-0.285	
	Cabernet franc 2015										-0.266					
Cave Spring	Cabernet franc 2014		0.240	0.232			0.270	-0.237		0.297	-0.295	-0.350	0.290	0.360		
	Cabernet franc 2015	-0.258		-0.231										0.263		
Coyote's Run	Pinot noir EW 2014						-0.329		-0.239		-0.372	-0.321			-0.305	-0.249
	Pinot noir EW 2015								-0.252							
	Pinot noir NS 2014										-0.357			0.259		
	Pinot noir NS 2015	0.331		0.271	0.342	0.303			-0.292	-0.245			-0.595			

2.8.2 SOIL MOISTURE AND LEAF Ψ REGRESSIONS

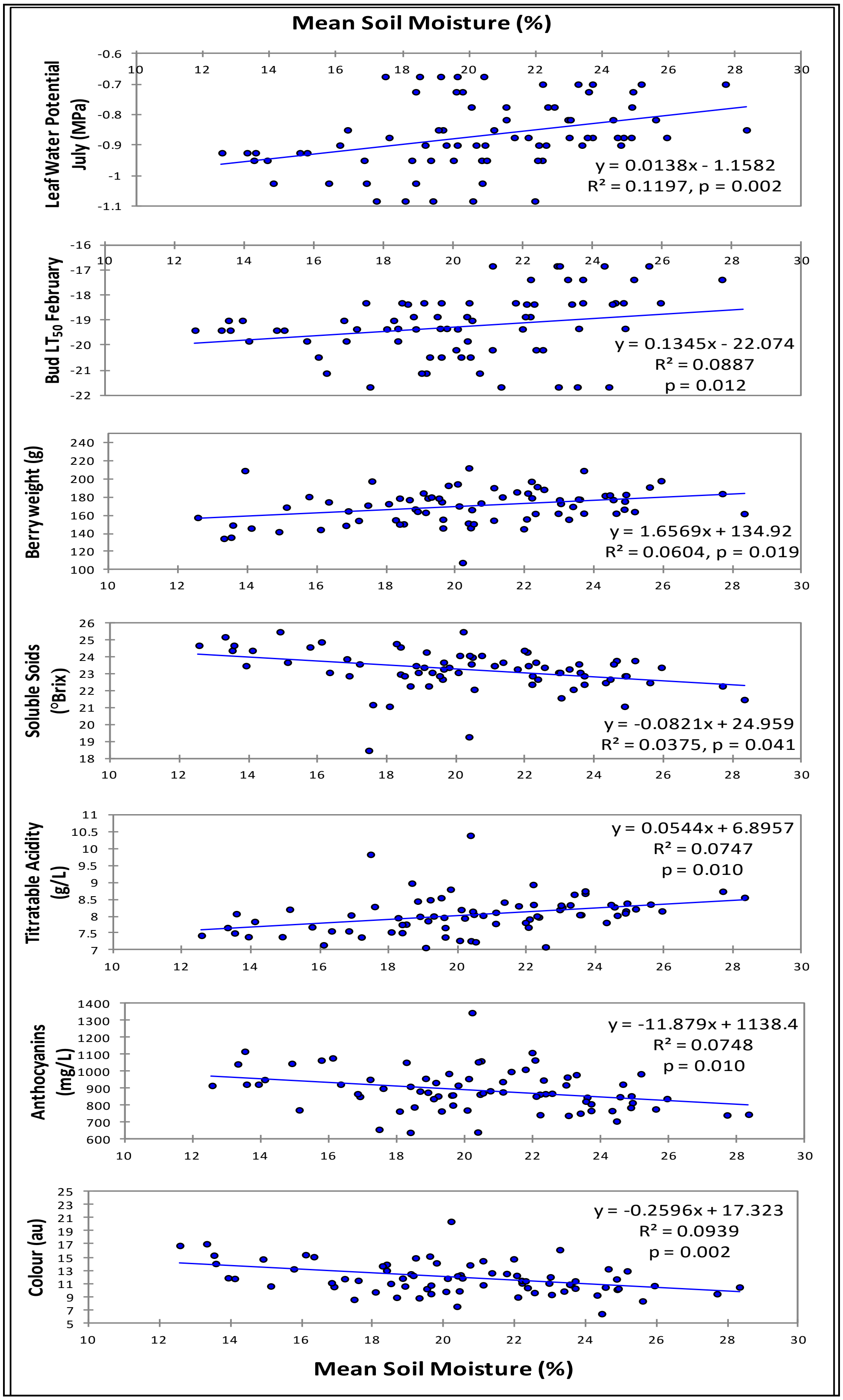

Figure 2.1 Cave Spring Cabernet franc 2014: Leaf water potential July (MPa), bud LT_{50} February, berry weight (g), soluble solids (°Brix), pH, titratable acidity (g/L), anthocyanins (mg/L), and colour (au) vs. mean soil moisture (%) scatterplot.

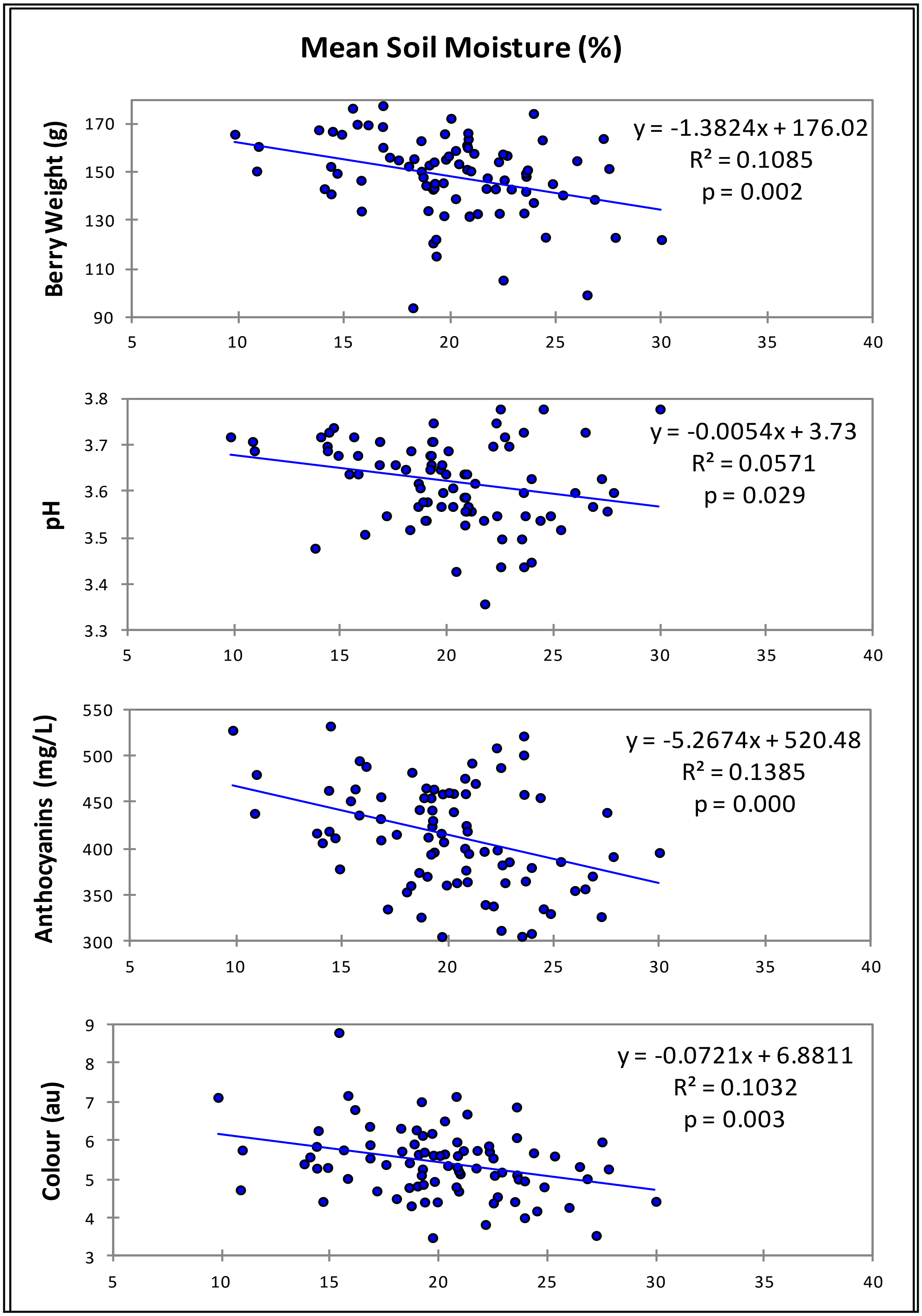

Figure 2.2 Coyote's Run Pinot noir East-West 2014: Berry weight (g), pH, anthocyanins (mg/L), and colour (au) vs. mean soil moisture (%) scatterplot.

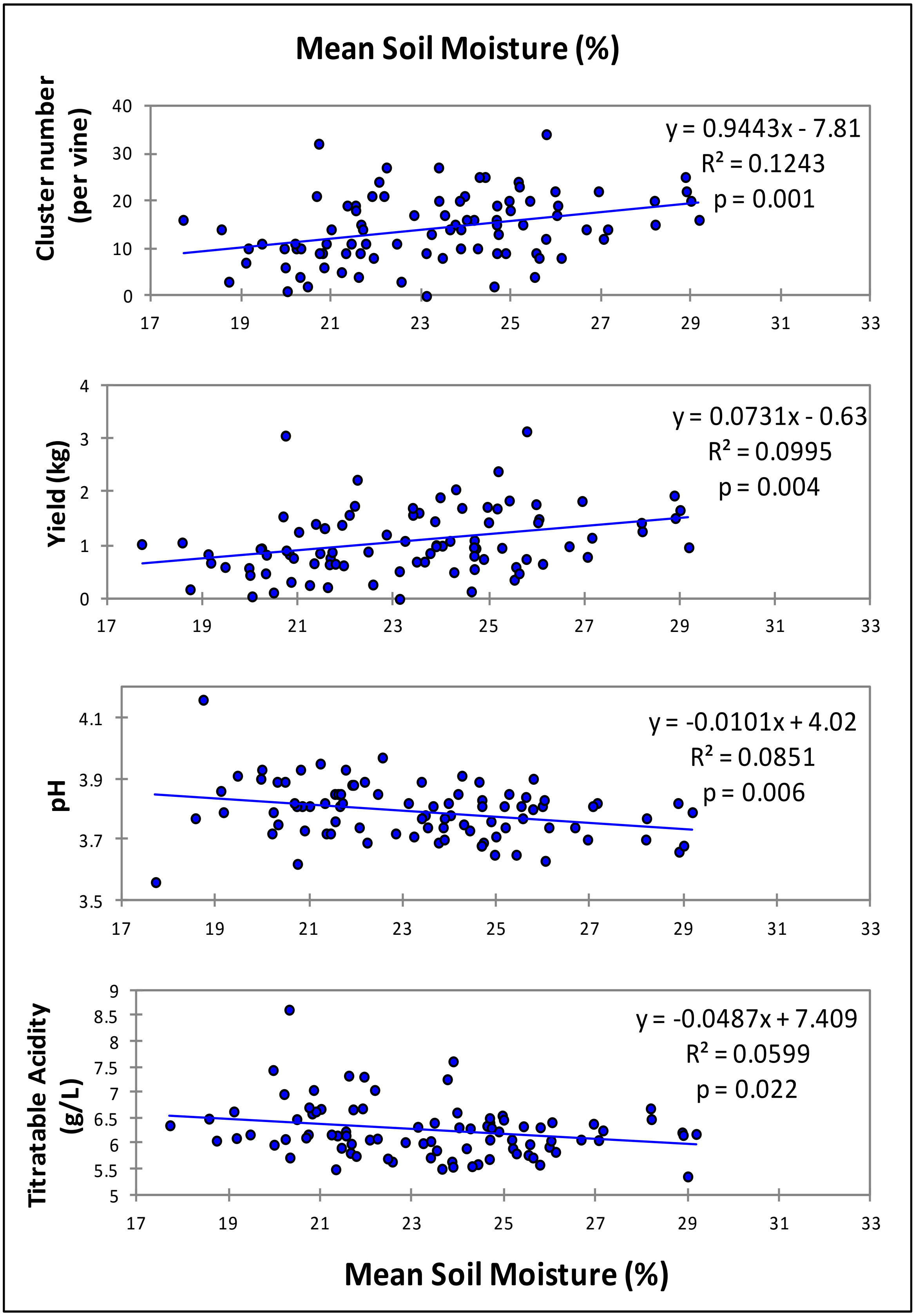

Figure 2.3 Coyote's Run Pinot noir North-South 2015: Cluster number (per vine), yield (kg), pH, and titratable acidity (g/L) vs. mean soil moisture (%) scatterplot.

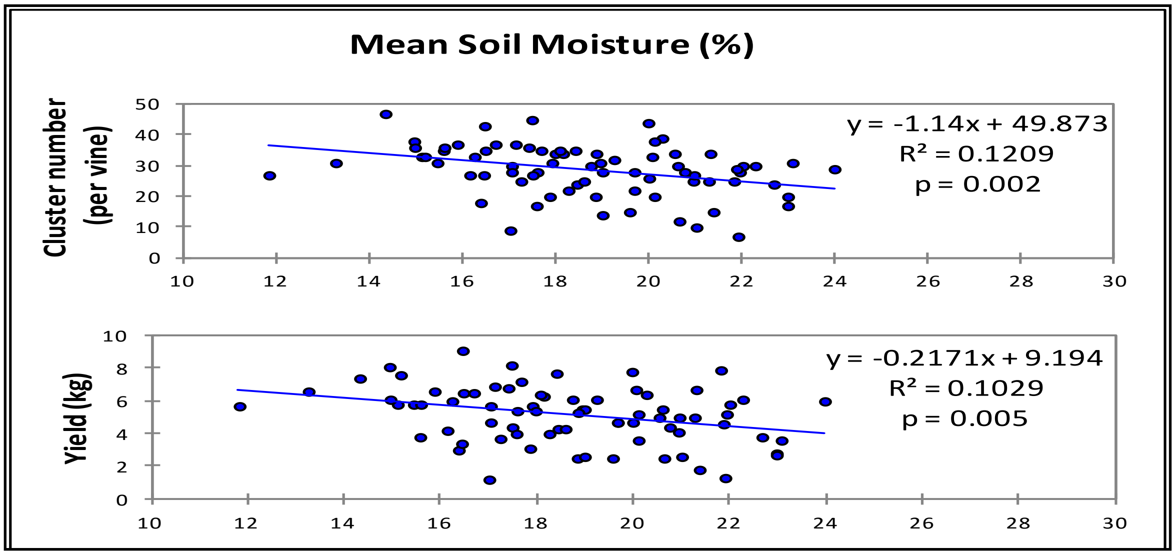

Figure 2.4 Cave Spring Riesling 2014: Cluster number (per vine), and yield (kg) vs. mean soil moisture (%) scatterplot.

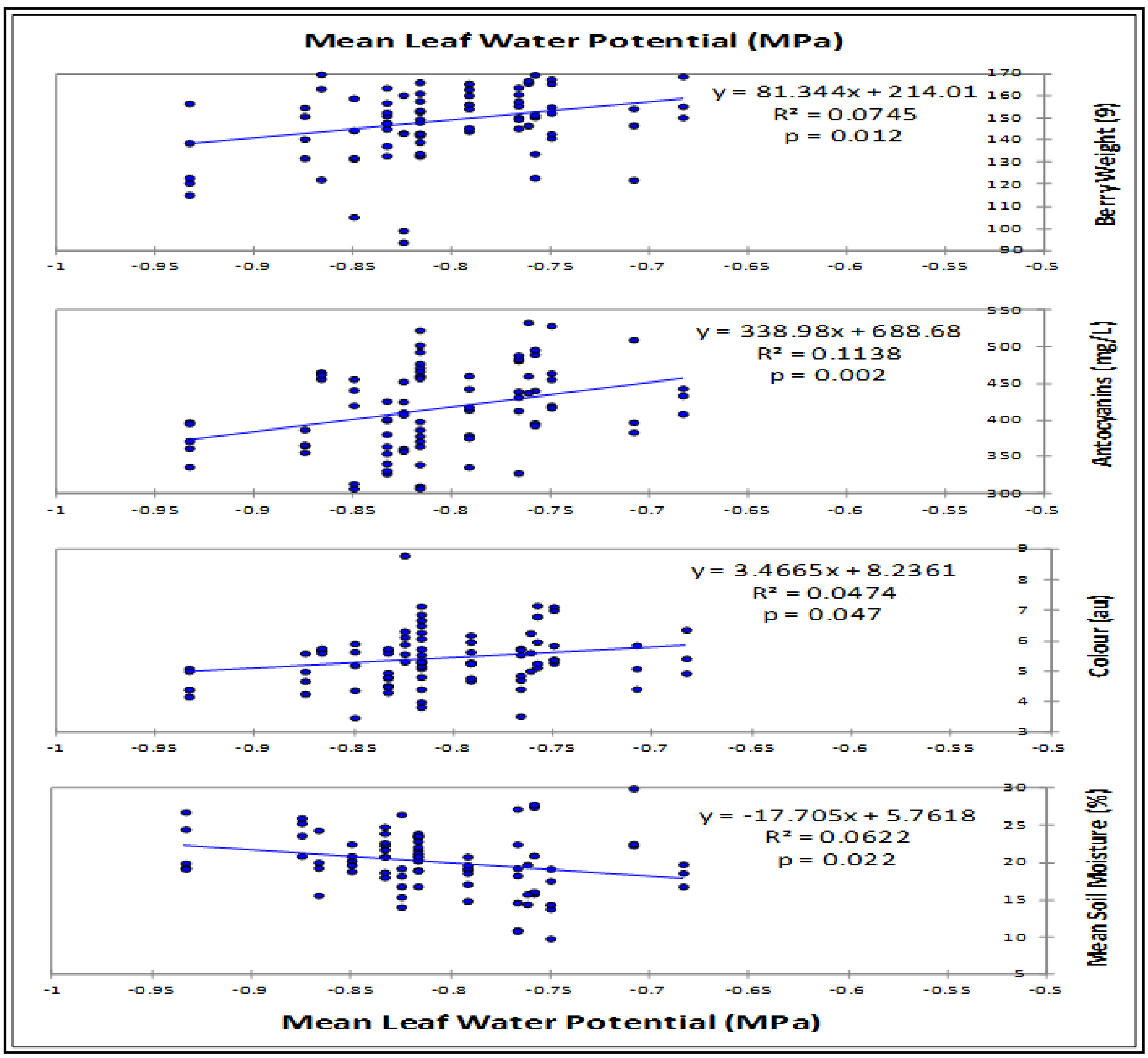

Figure 2.5 Coyote's Run Pinot noir East-West 2014: Berry weight (g), anthocyanin concentration (mg/L), colour (au), and mean soil moisture (%) vs. mean leaf water potential (MPa) scatterplot.

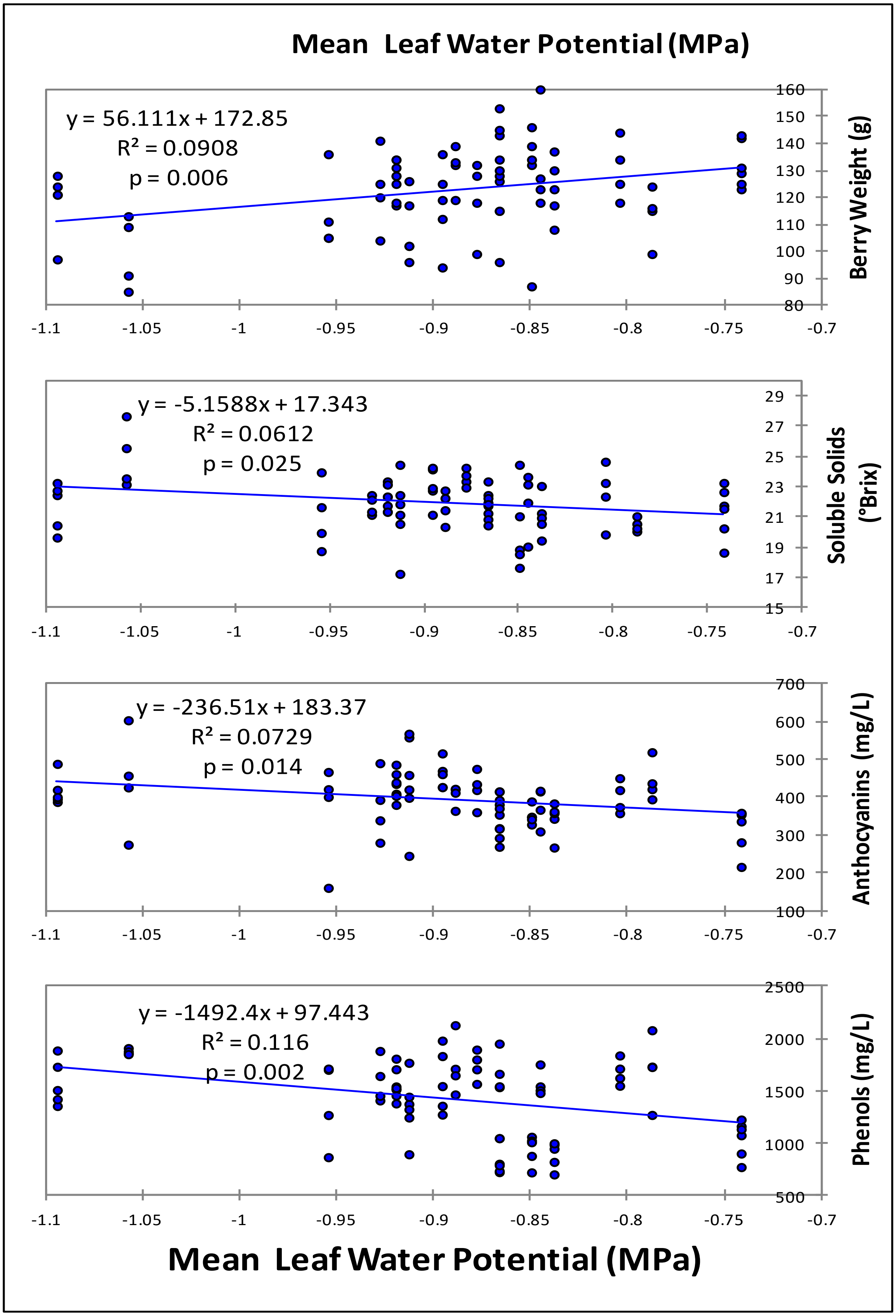

Figure 2.6 Coyote's Run Pinot noir East-West 2015: Berry weight (g), soluble solids (°Brix), anthocyanin concentration (mg/L), and phenols (mg/L) vs. mean leaf water potential (MPa) scatterplot.

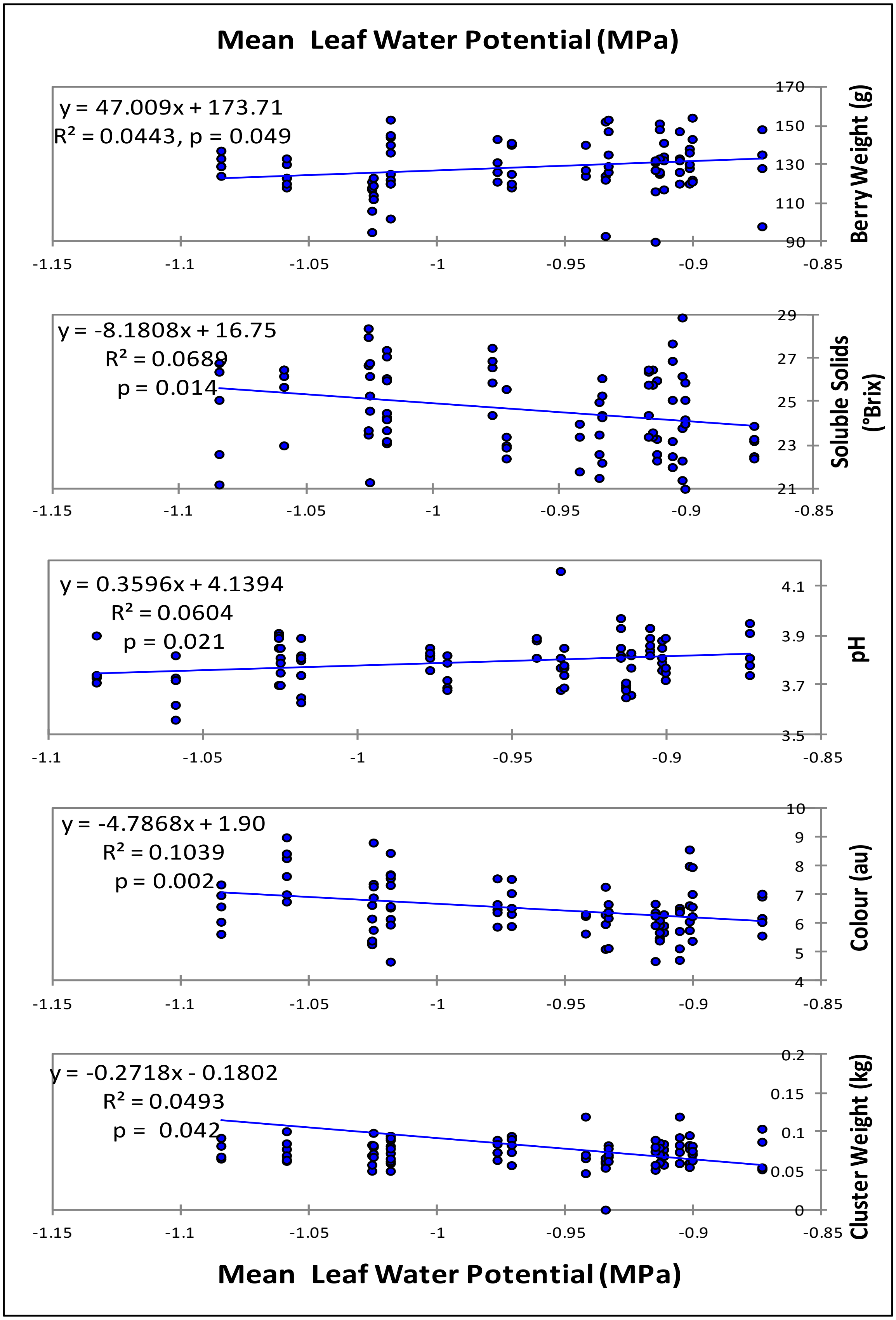

Figure 2.7 Coyote's Run Pinot noir North-South 2015: Berry weight (g), soluble solids (°Brix), pH, colour (au), and cluster weight (kg) vs. mean leaf water potential (MPa) scatterplot.

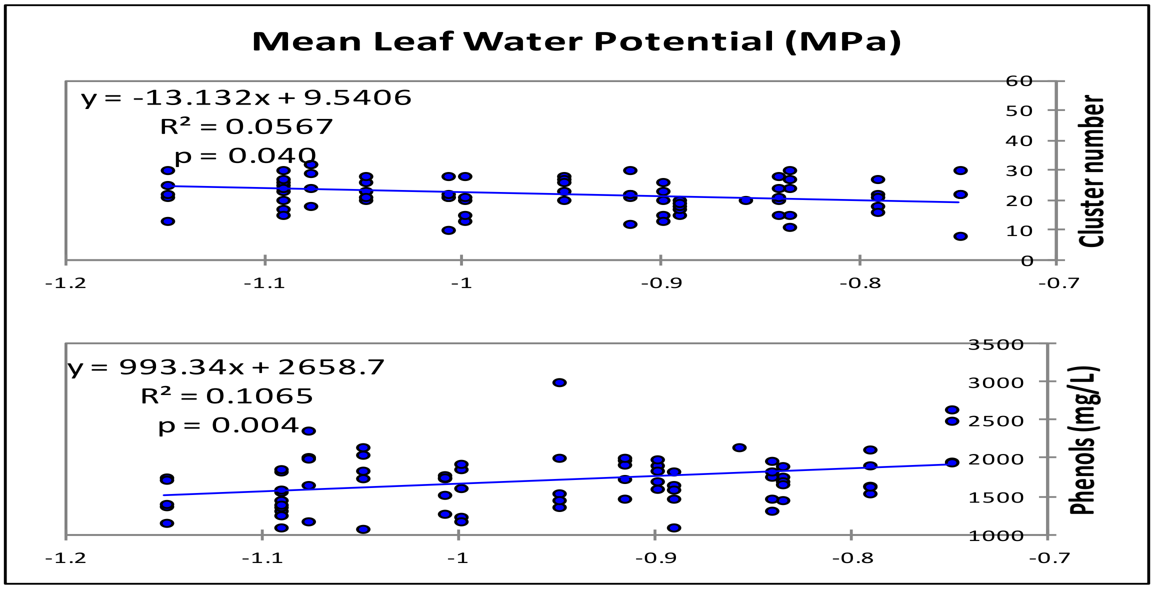

Figure 2.8 Cave Spring Cabernet franc 2014: Cluster number (per vine), and phenols vs. mean leaf water potential (MPa) scatterplot.

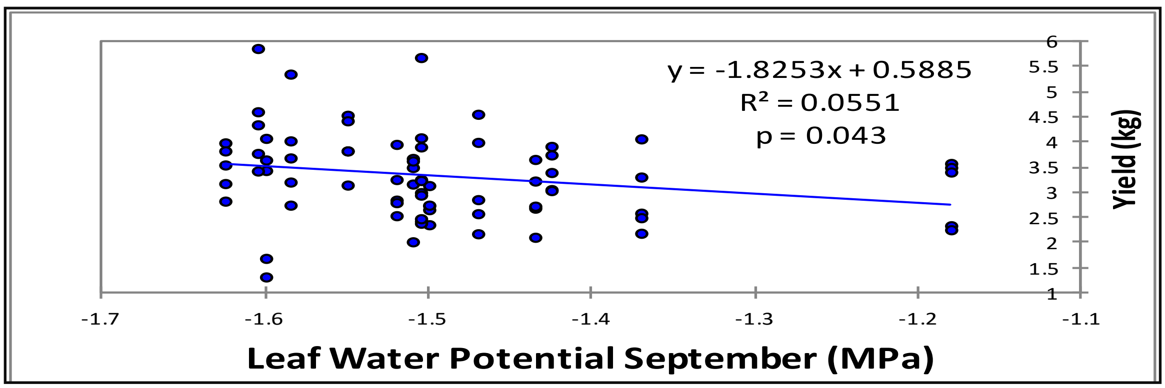

Figure 2.9 Cave Spring Cabernet franc 2015: Yield (kg) vs. mean leaf water potential (MPa) scatterplot.

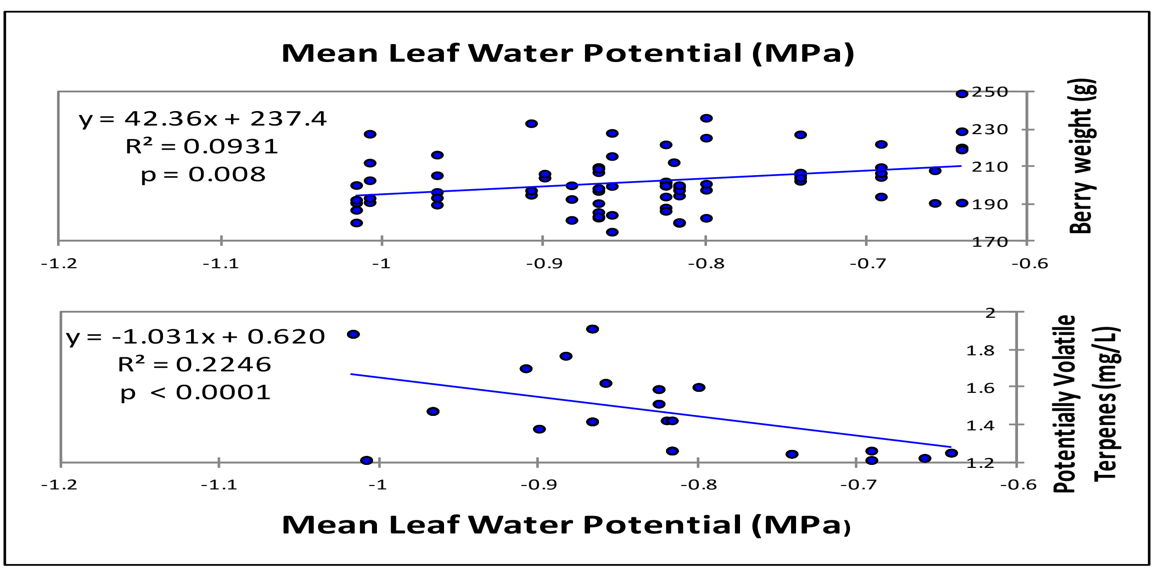

Figure 2.10 Cave Spring Riesling 2014: Berry weight (g), and potentially volatile terpenes (mg/L) vs. mean leaf water potential (MPa) scatterplot.

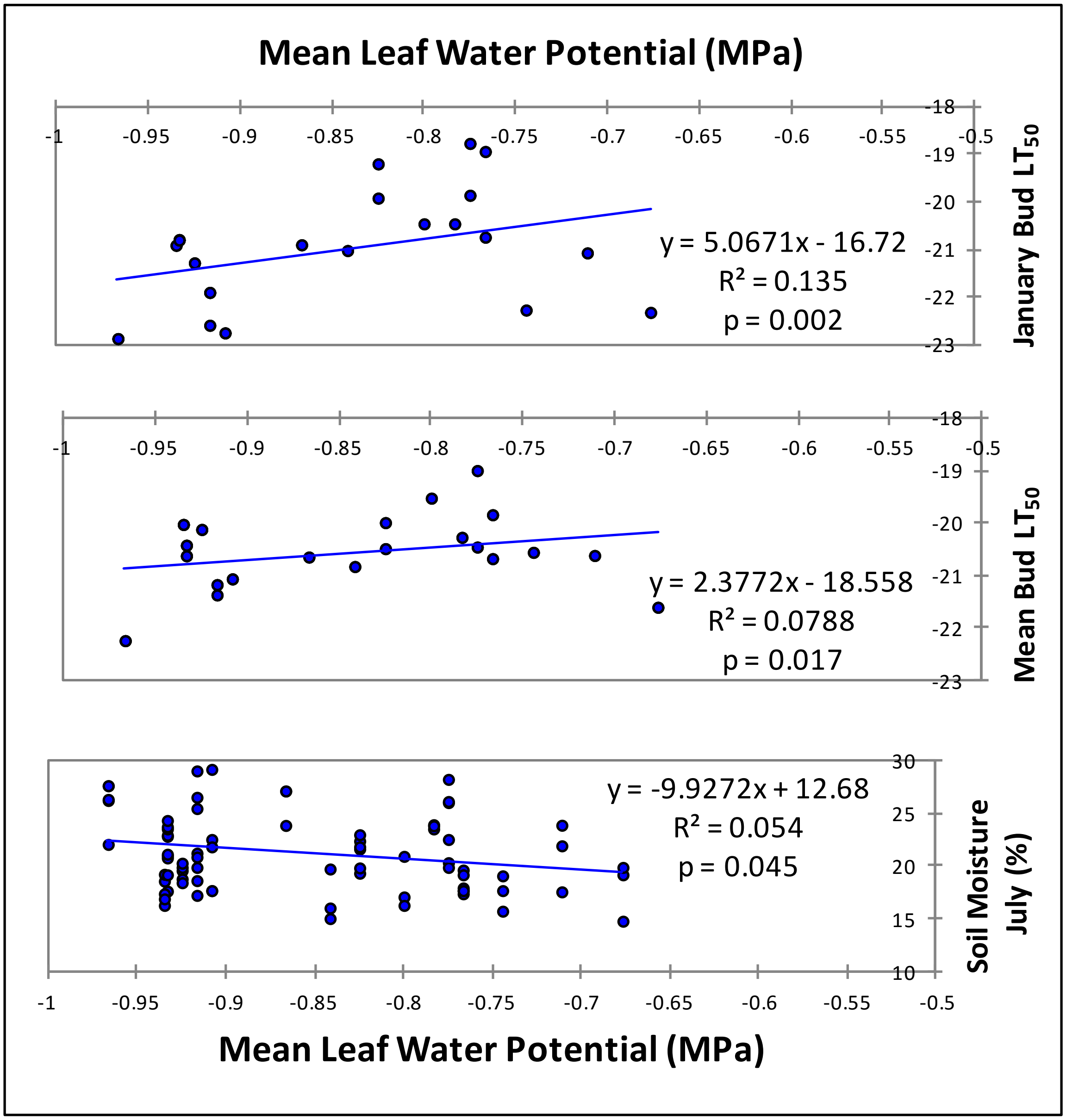

Figure 2.11 Lambert Cabernet franc 2014: January bud LT_{50}, mean bud LT_{50}, and soil moisture July (%) vs. mean leaf water potential (MPa) scatterplot.

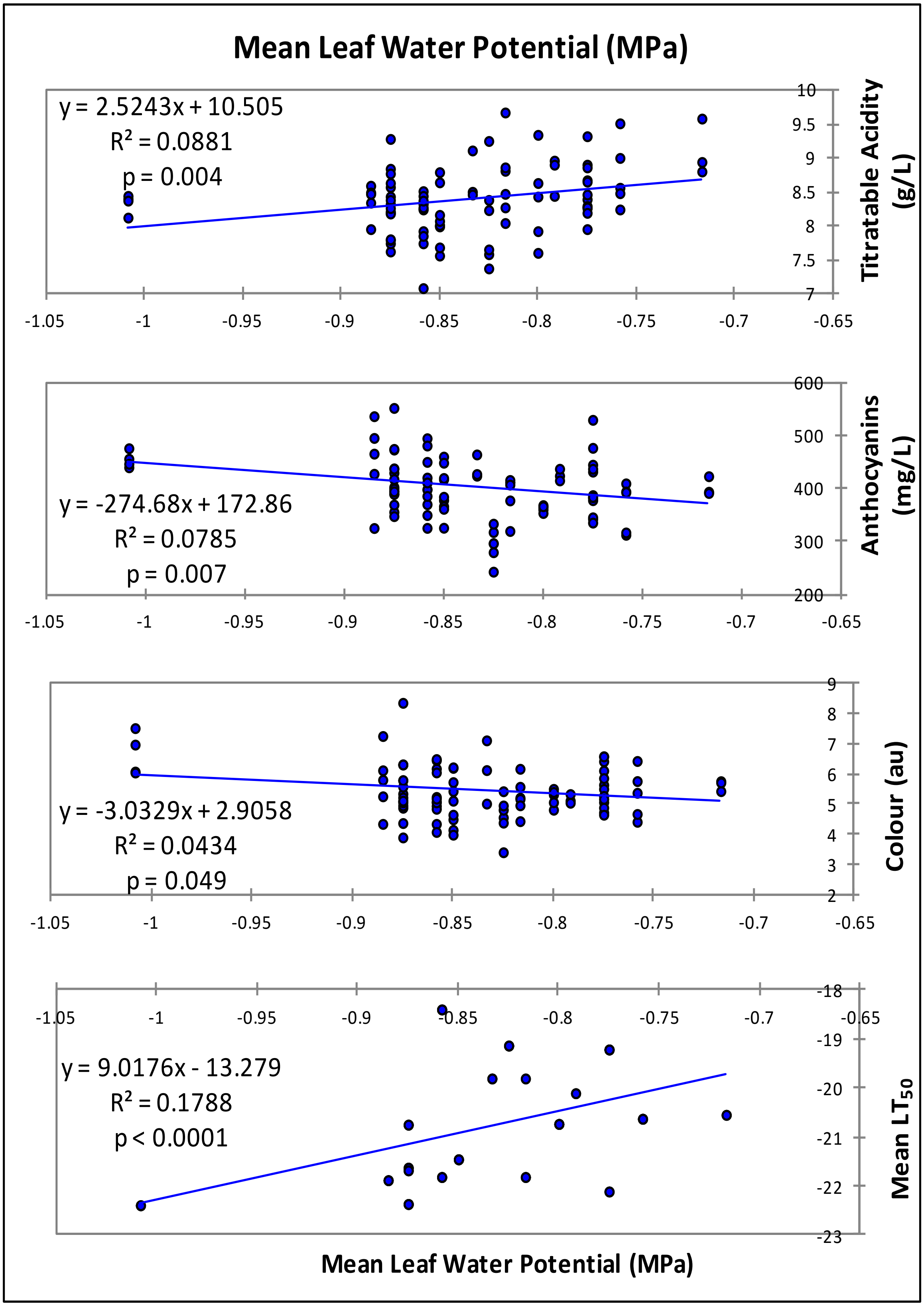

Figure 2.12 Coyote's Run Pinot noir North-South 2014: Titratable acidity (g/L), anthocyanins (mg/L), colour (au), and mean LT_{50} vs. mean leaf water potential (MPa) scatterplot.

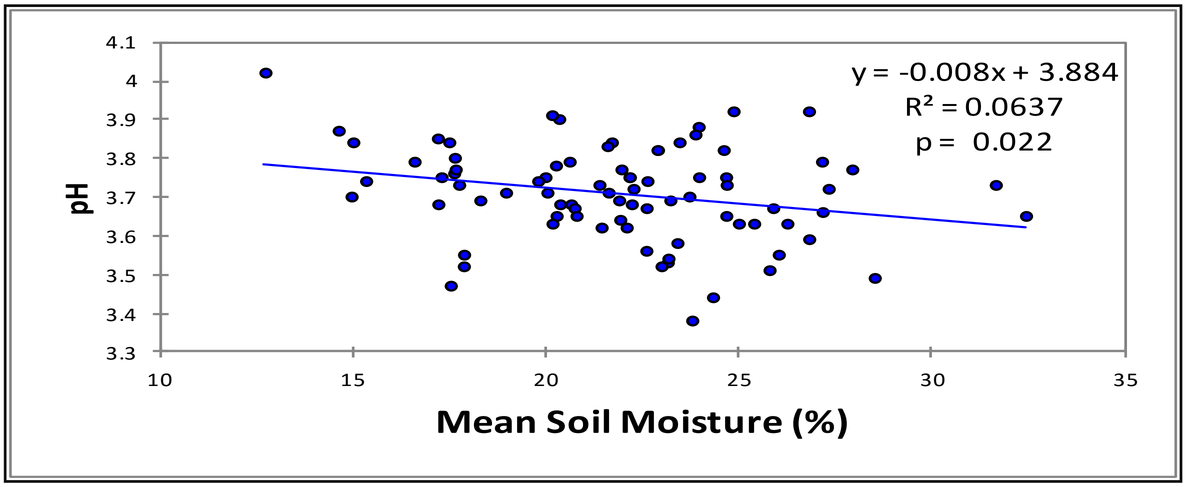

Figure 2.13 Coyote's Run Pinot noir East-West 2015: pH vs. mean soil moisture (%) scatterplot.

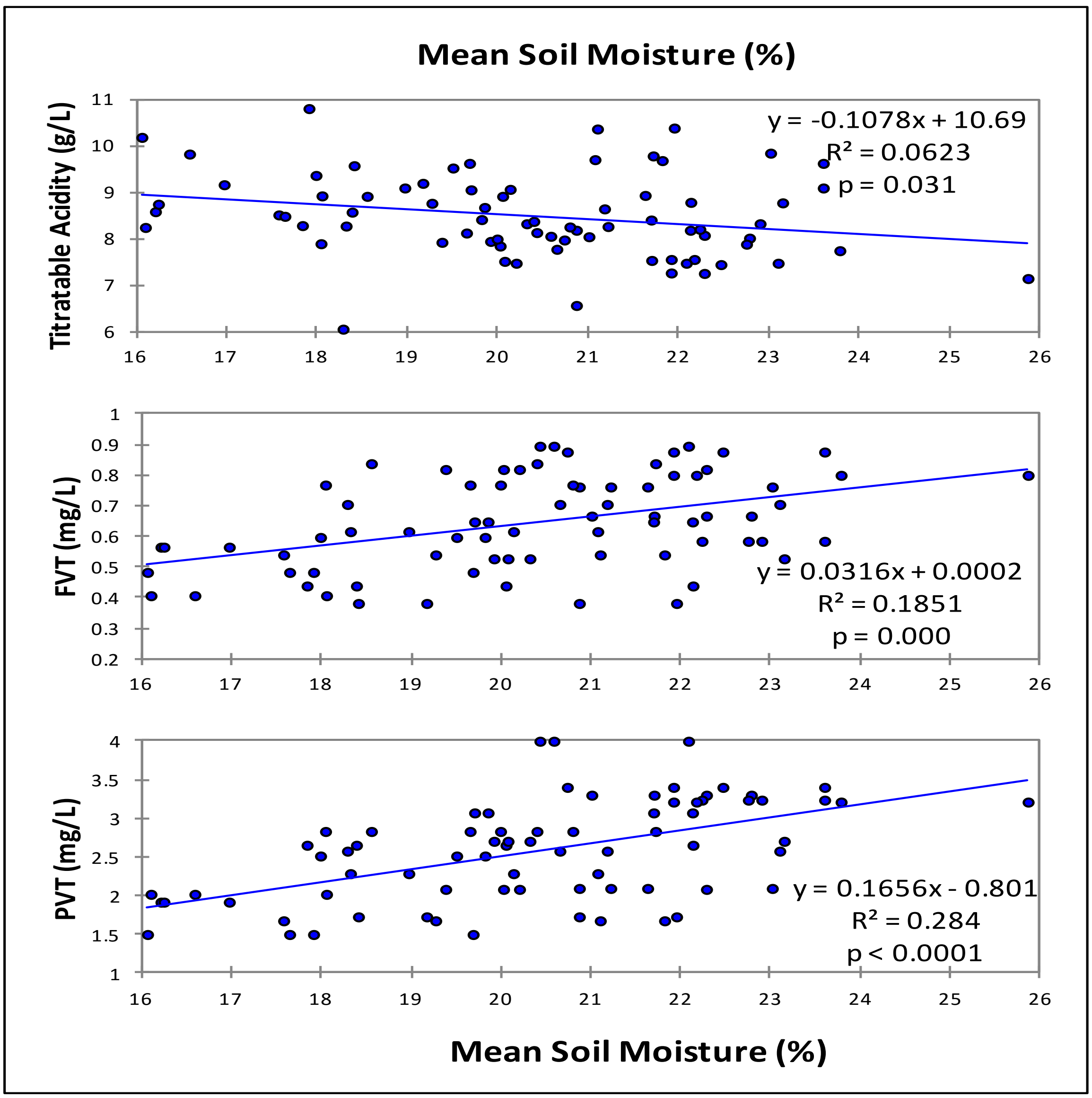

Figure 2.14 Lambert Riesling 2015: Titratable acidity (g/L), free-volatile, and potentially-volatile terpenes (mg/L) vs. mean soil moisture (%) scatterplot.

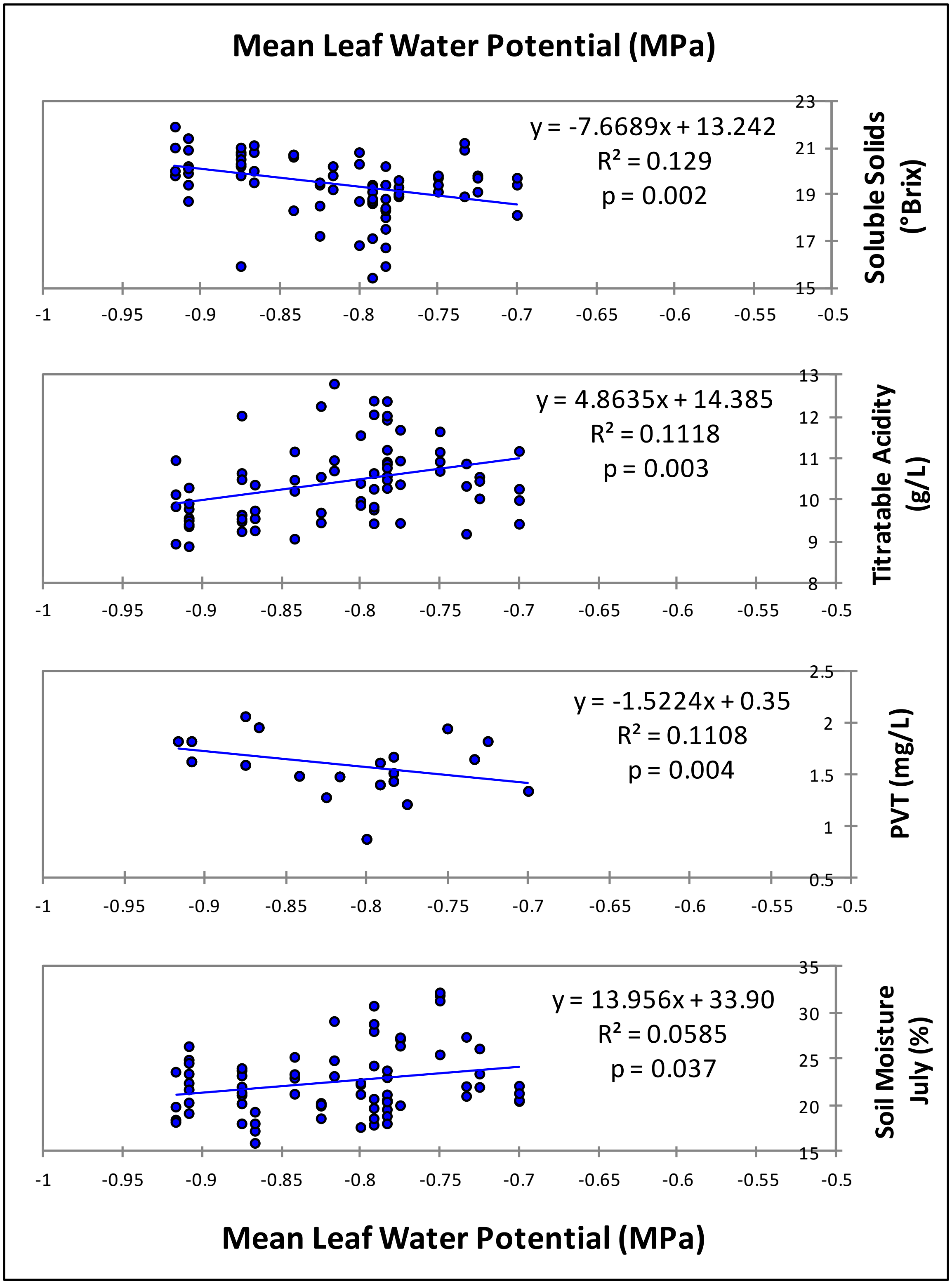

Figure 2.15 Lambert Riesling 2014: Soluble solids (°Brix), titratable acidity (g/L), potentially volatile terpenes (mg/L), and soil moisture July (%) vs. mean leaf water potential (MPa) scatterplot.

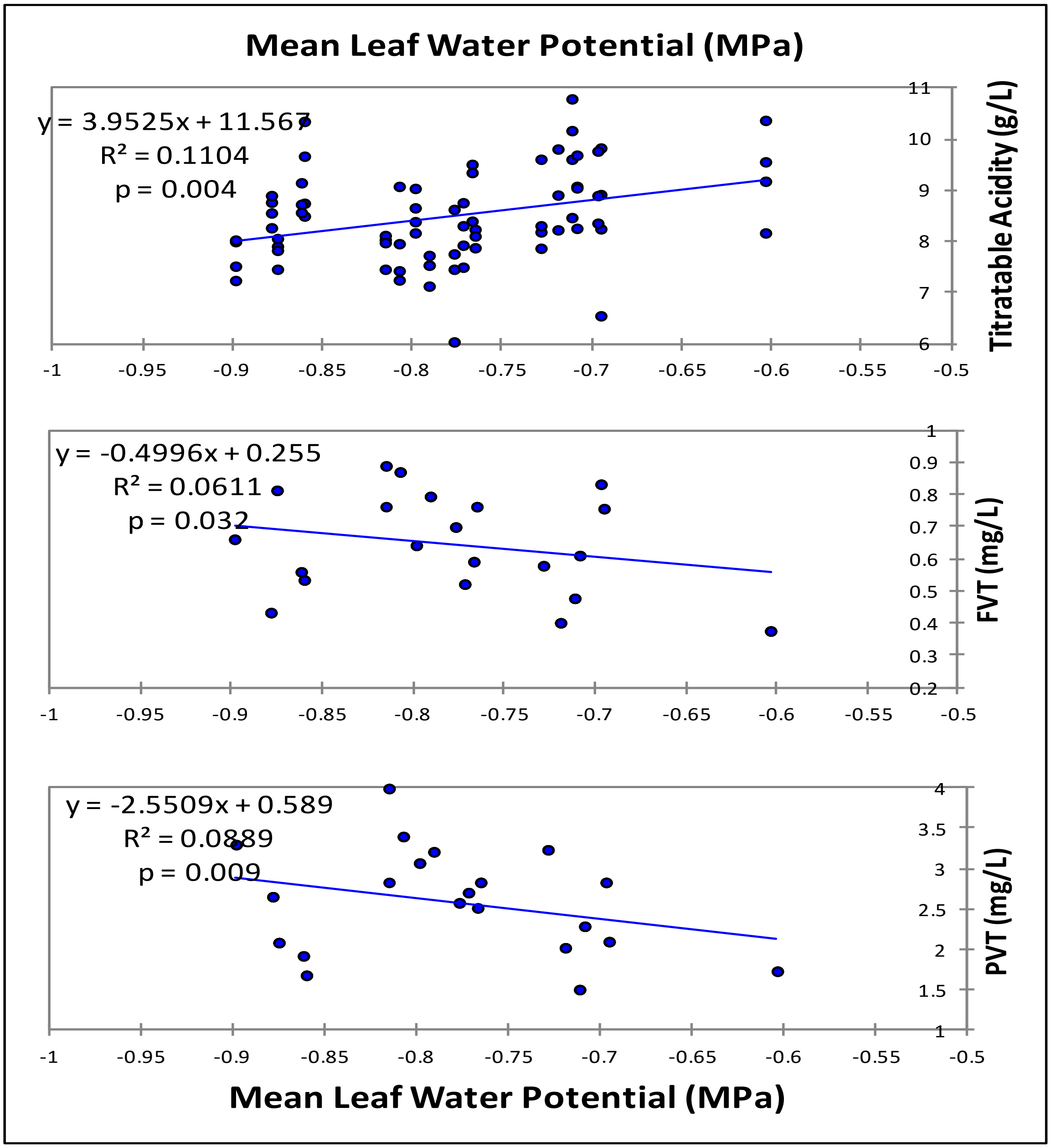

Figure 2.16 Lambert Riesling 2015: Titratable acidity (g/L), free volatile, and potentially-volatile terpenes (mg/L) vs. mean leaf water potential (MPa) scatterplot.

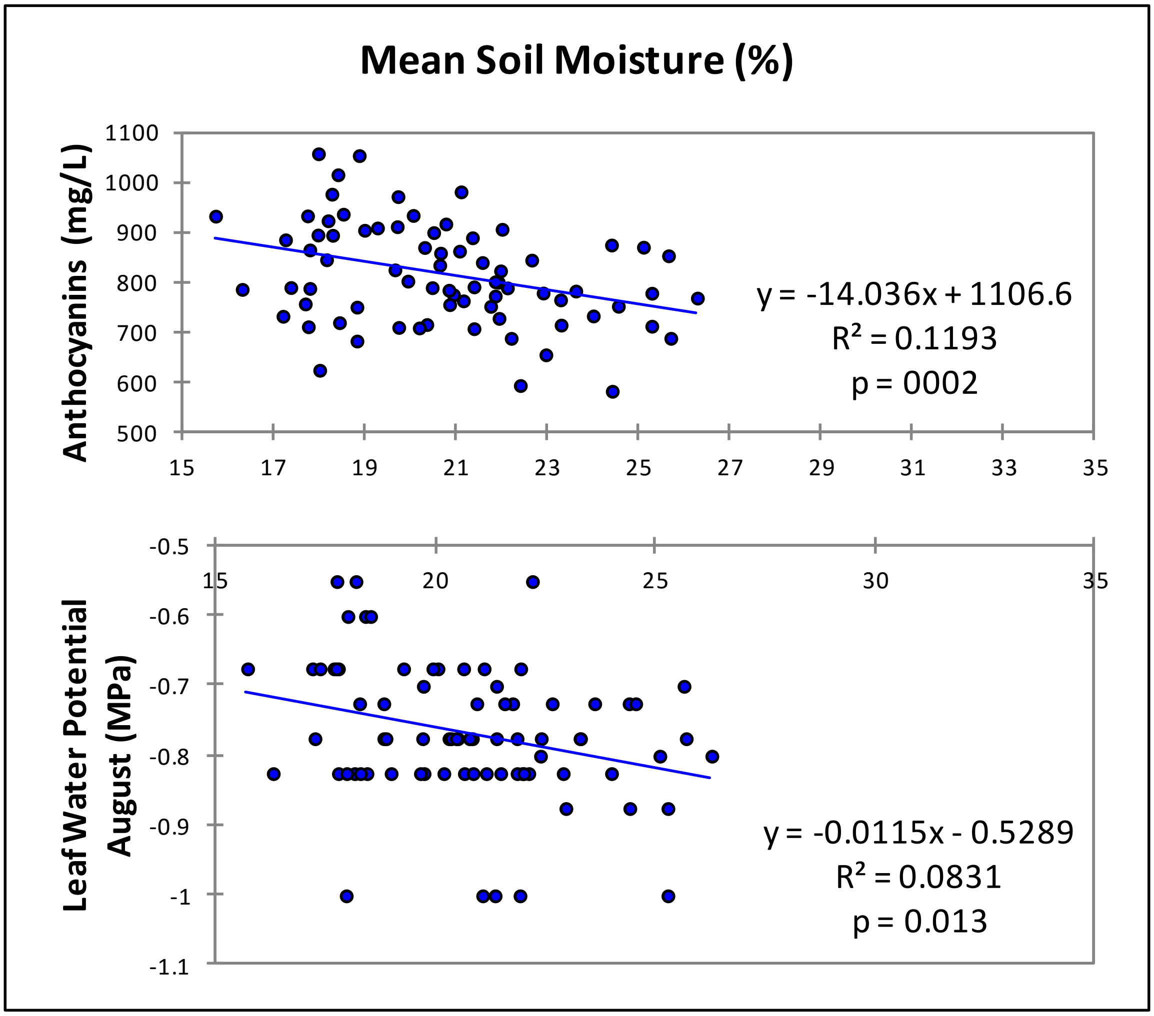

Figure 2.17 Lambert Cabernet franc 2014: Anthocyanin concentration (mg/L), and leaf water potential August (MPa) vs. mean soil moisture (%) scatterplot.

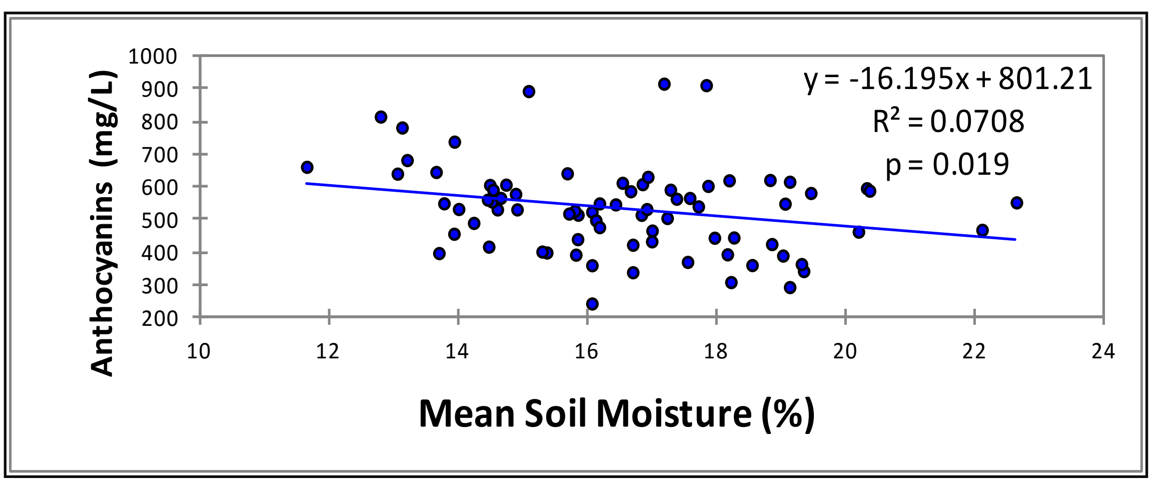

Figure 2.18 Lambert Cabernet franc 2015: Anthocyanin concentration (mg/L) vs. mean soil moisture (%) scatterplot.

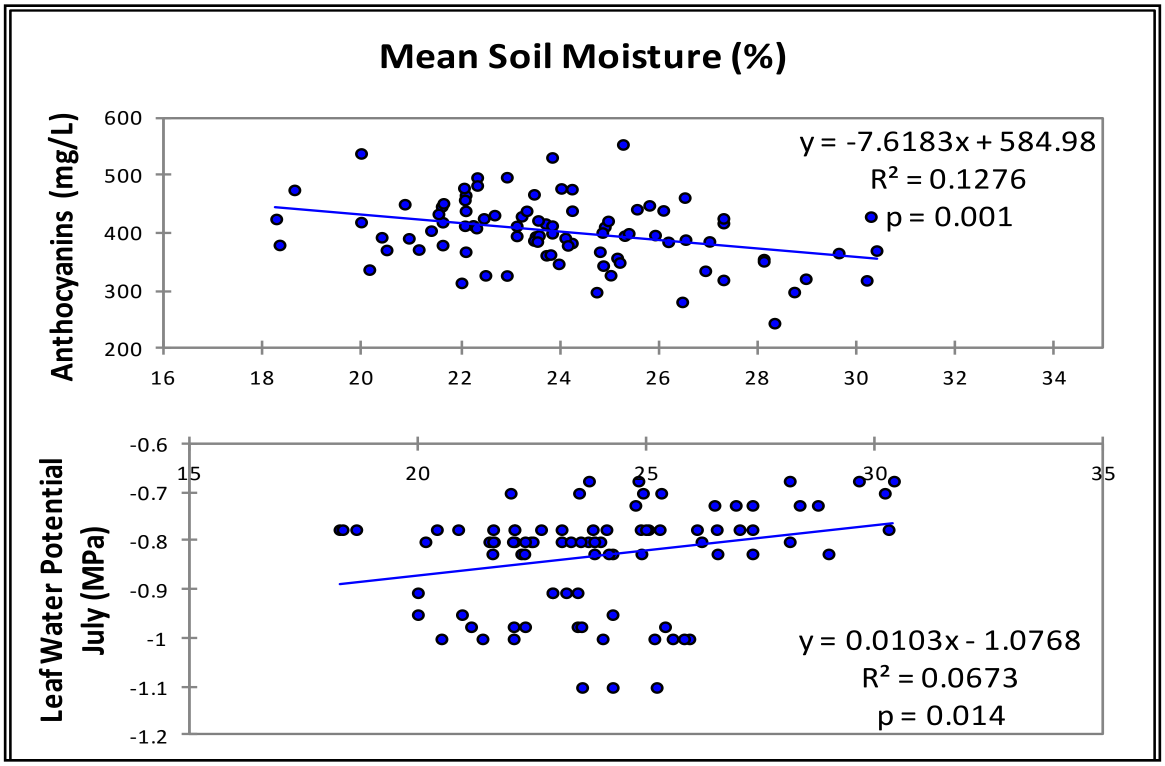

Figure 2.19 Coyote's Run Pinot noir North-South 2014: Anthocyanin concentration (mg/L) and leaf water potential July (MPa) vs. mean soil moisture (%) scatterplot**.**

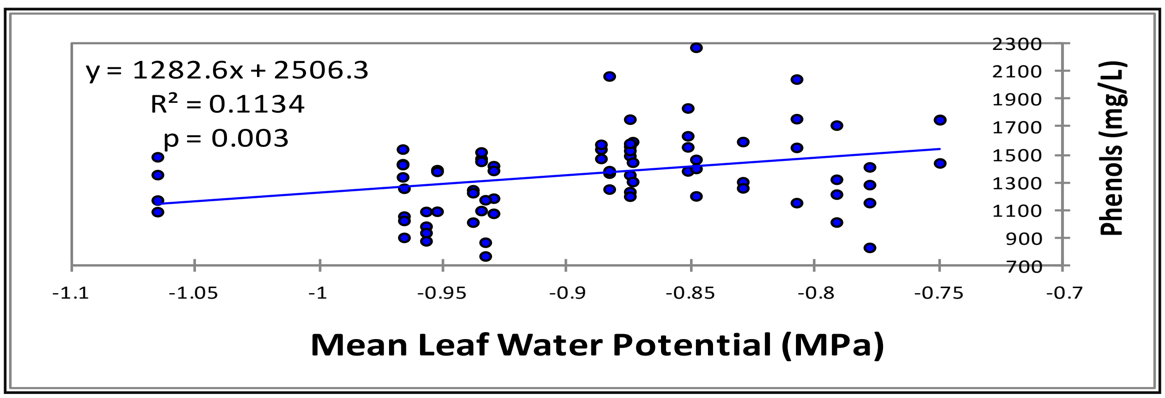

Figure 2.20 Lambert Cabernet franc 2015: Phenols (mg/L) vs. mean leaf water potential (MPa) scatterplot.

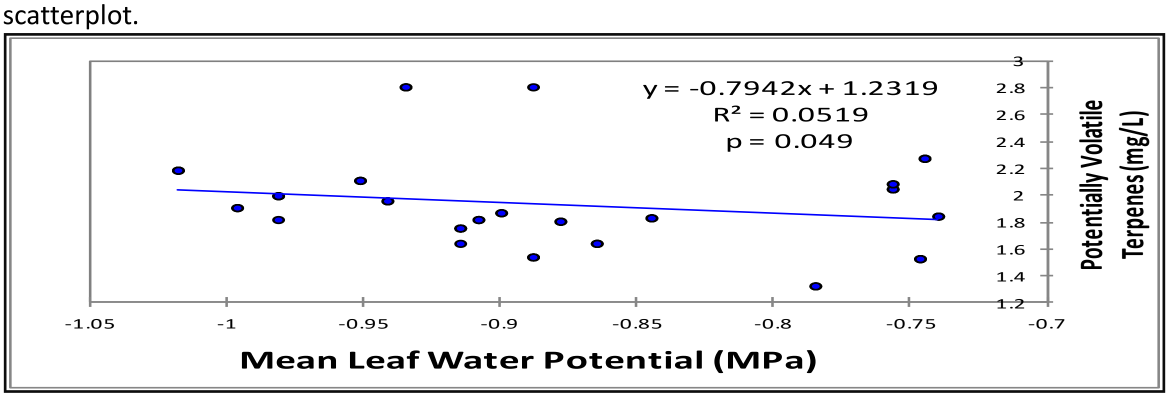

Figure 2.21 Cave Spring Riesling 2015: Potentially volatile terpenes (mg/L) vs. mean leaf water potential (MPa) scatterplot.

2.8.3 PRINCIPAL COMPONENT ANALYSIS

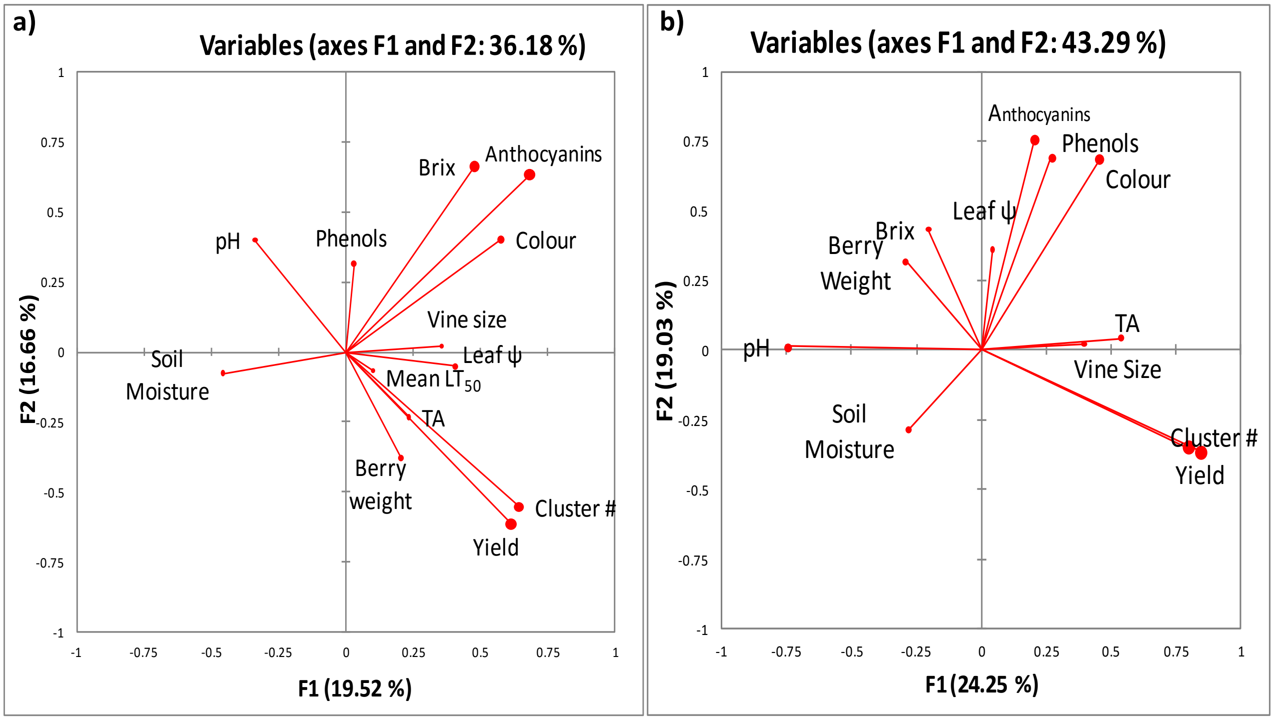

Figure 2.22 Principal component analysis for Lambert Cabernet franc: a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and winter hardiness (mean LT_{50}). Abbreviations: TA=Titratable acidity.

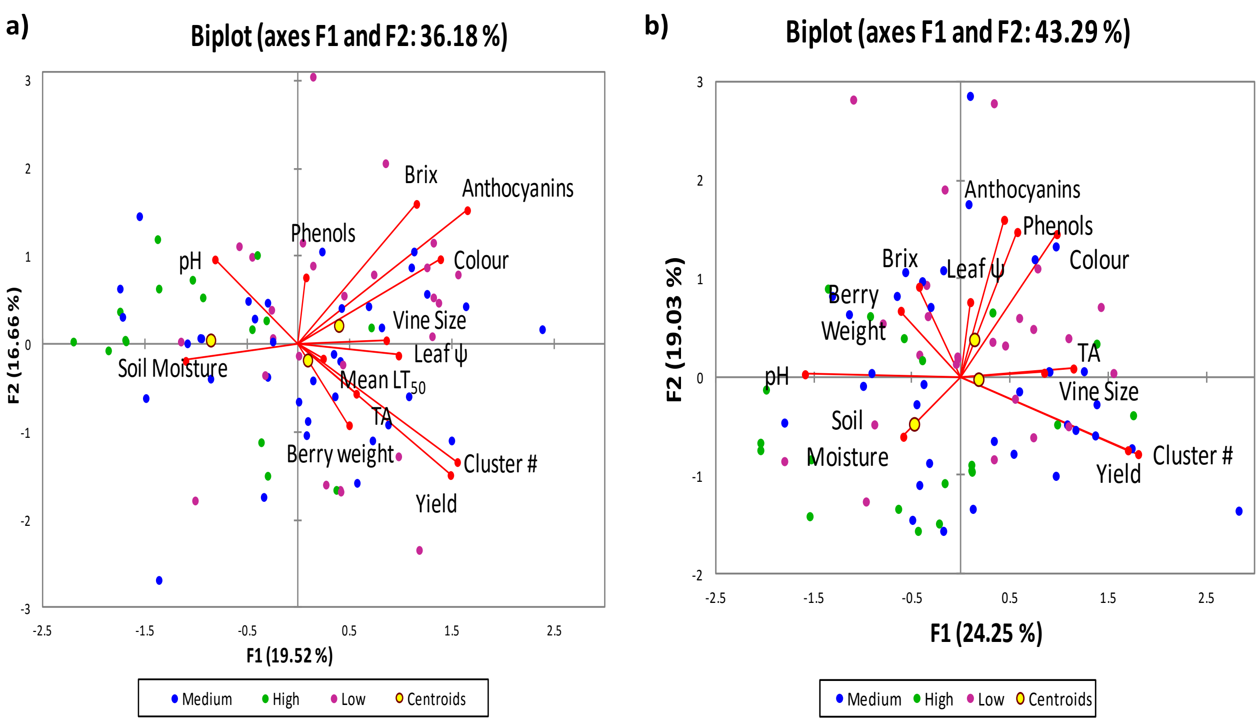

Figure 2.23 Principal component analysis correlation biplot of observations for Lambert Cabernet franc: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high soil moisture levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

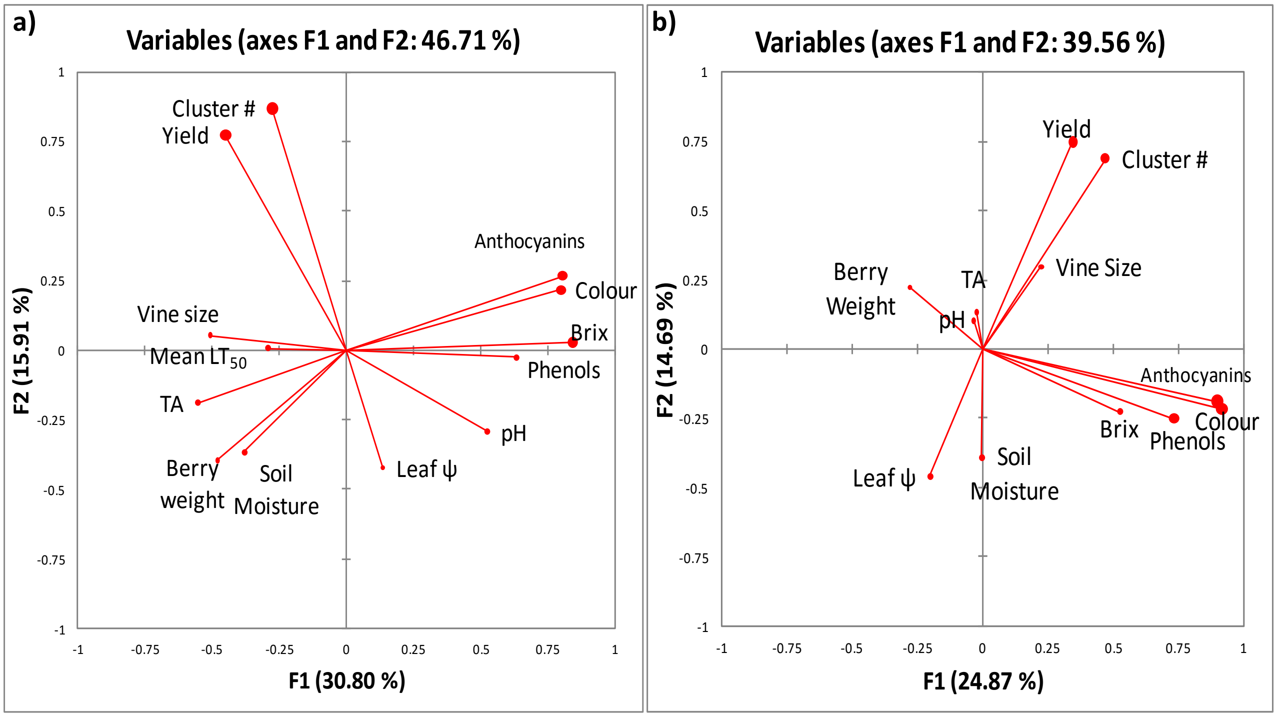

Figure 2.24 Principal component analysis for Cave Spring Cabernet franc: a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and winter hardiness (mean LT_{50}). Abbreviations: TA=Titratable acidity.

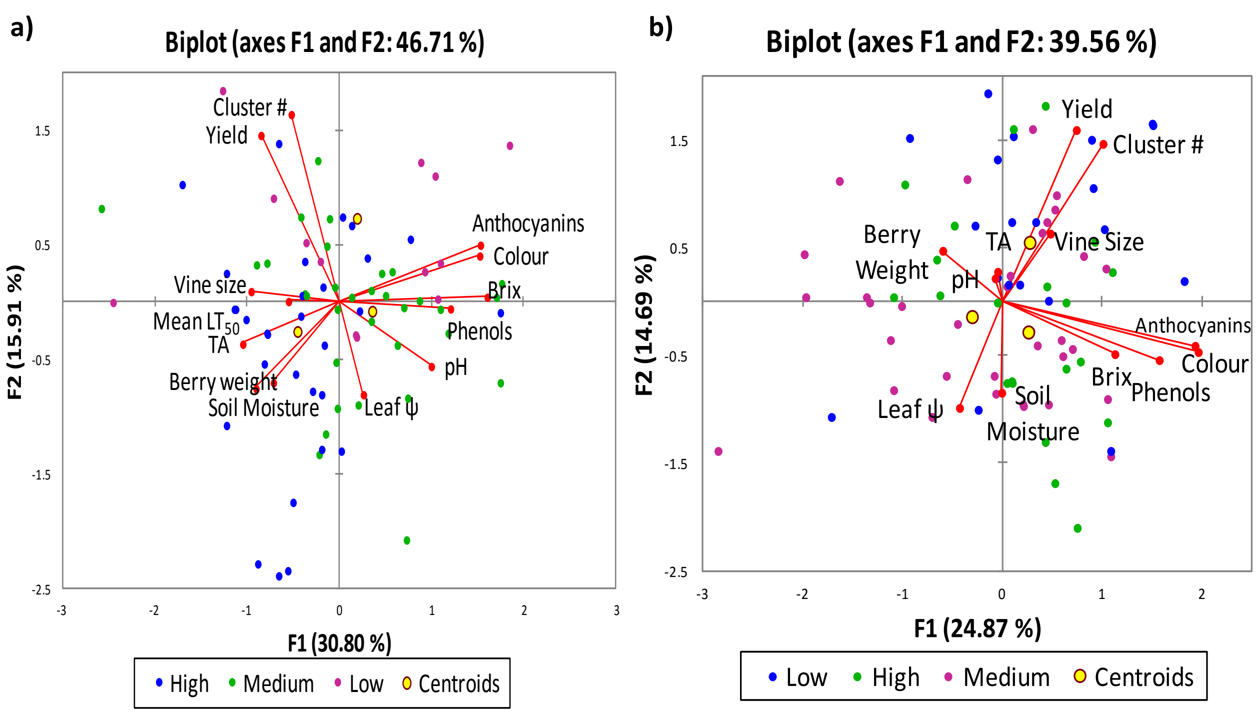

Figure 2.25 Principal component analysis correlation biplot of observations for Cave Spring Cabernet franc: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high soil moisture levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

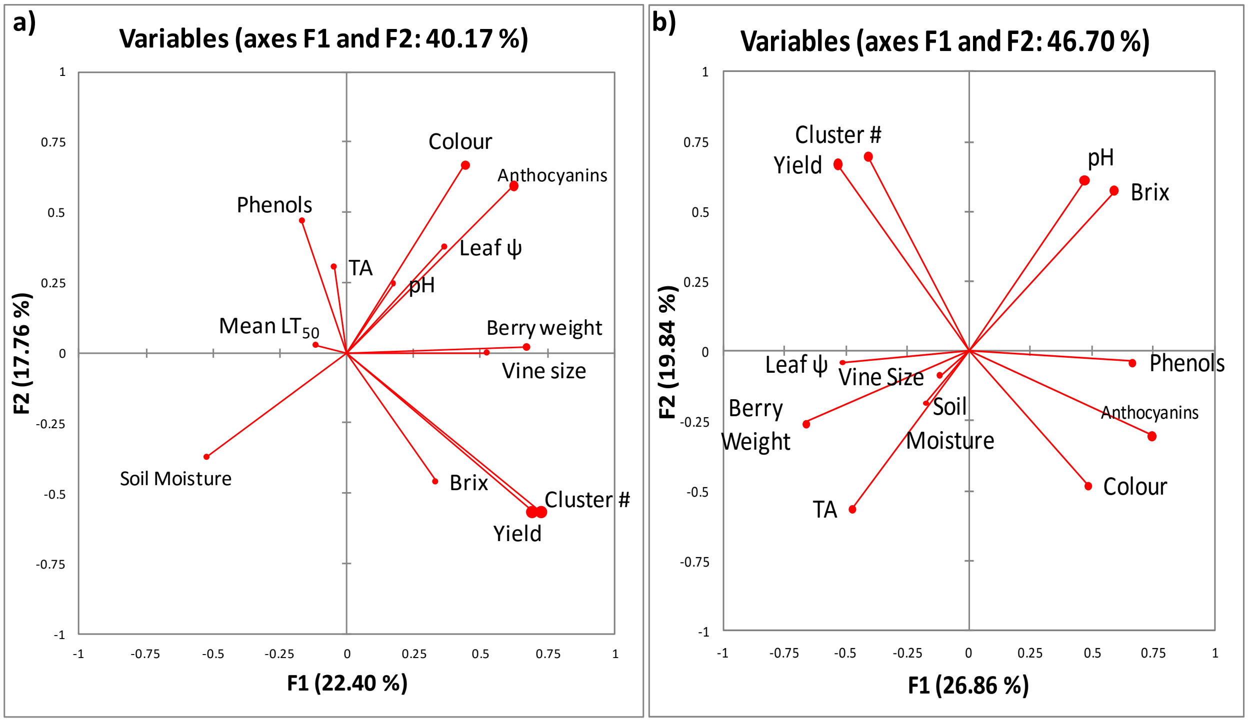

Figure 2.26 Principal component analysis for Coyote's Run Pinot noir (East-West): a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and winter hardiness (mean LT_{50}). Abbreviations: TA=Titratable acidity.

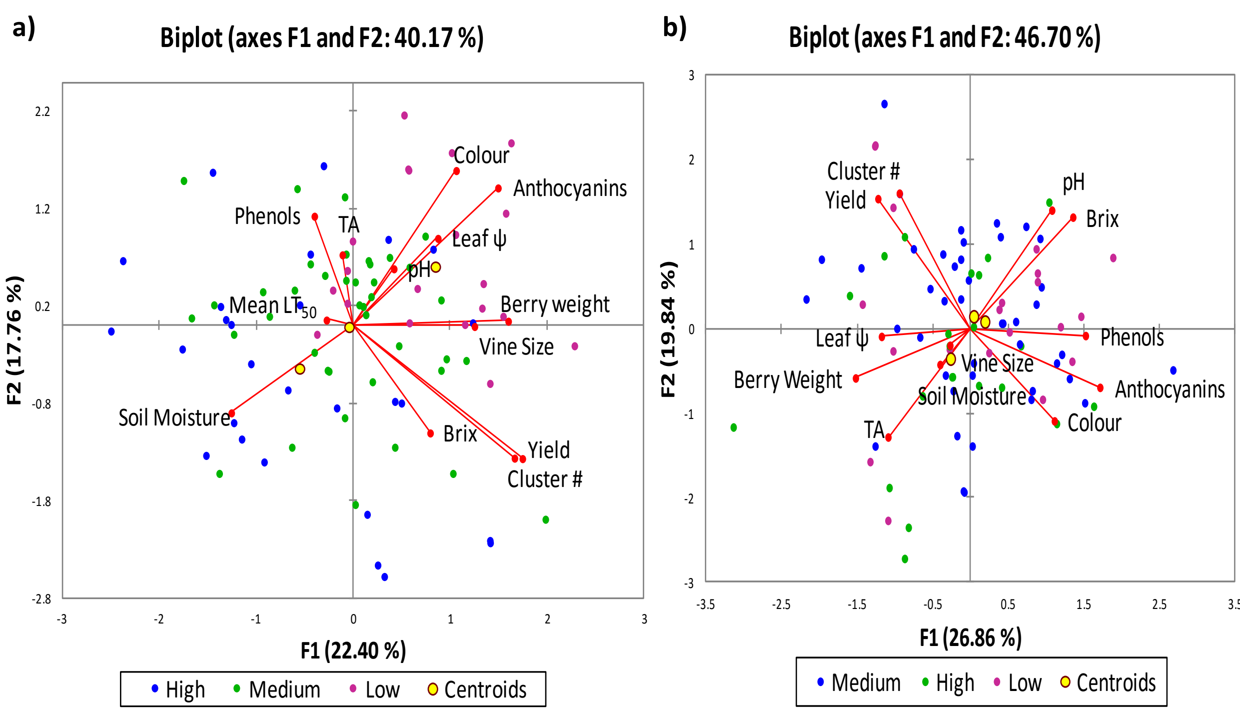

Figure 2.27 Principal component analysis correlation biplot of observations for Coyote's Run Pinot noir (East-West): a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high soil moisture levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

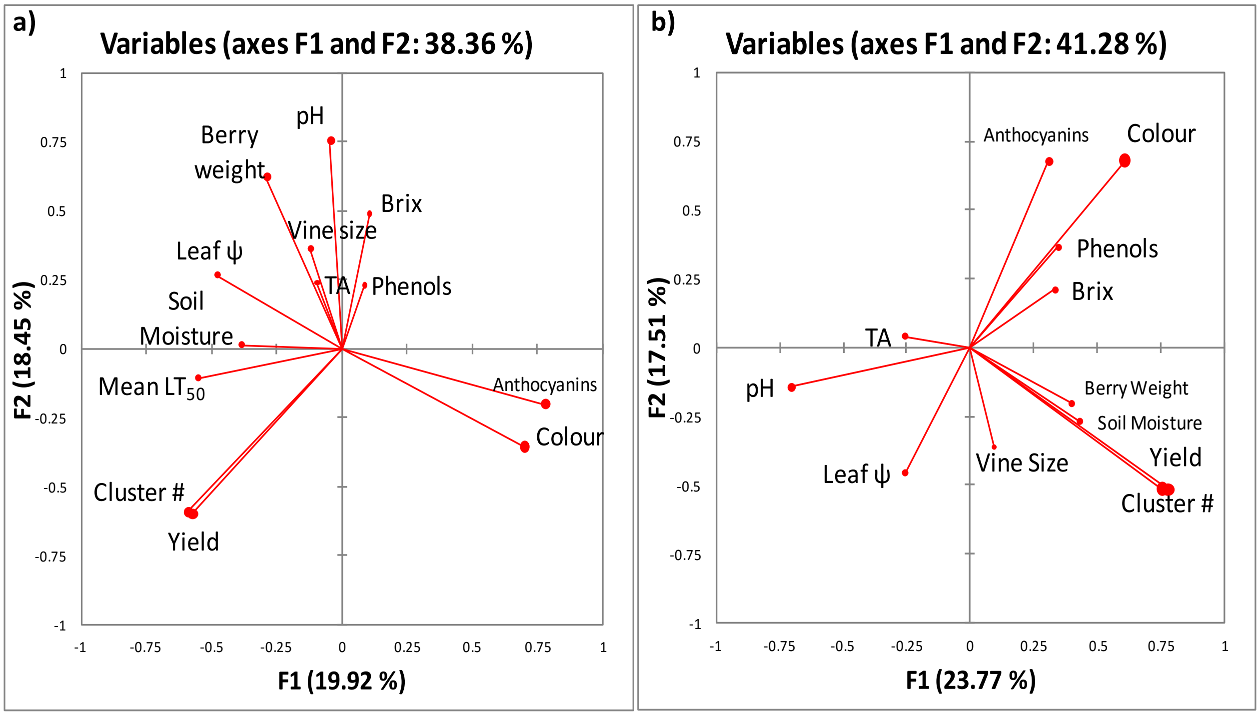

Figure 2.28 Principal component analysis for Coyote's Run Pinot noir (North-South): a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and winter hardiness (mean LT_{50}). Abbreviations: TA=Titratable acidity.

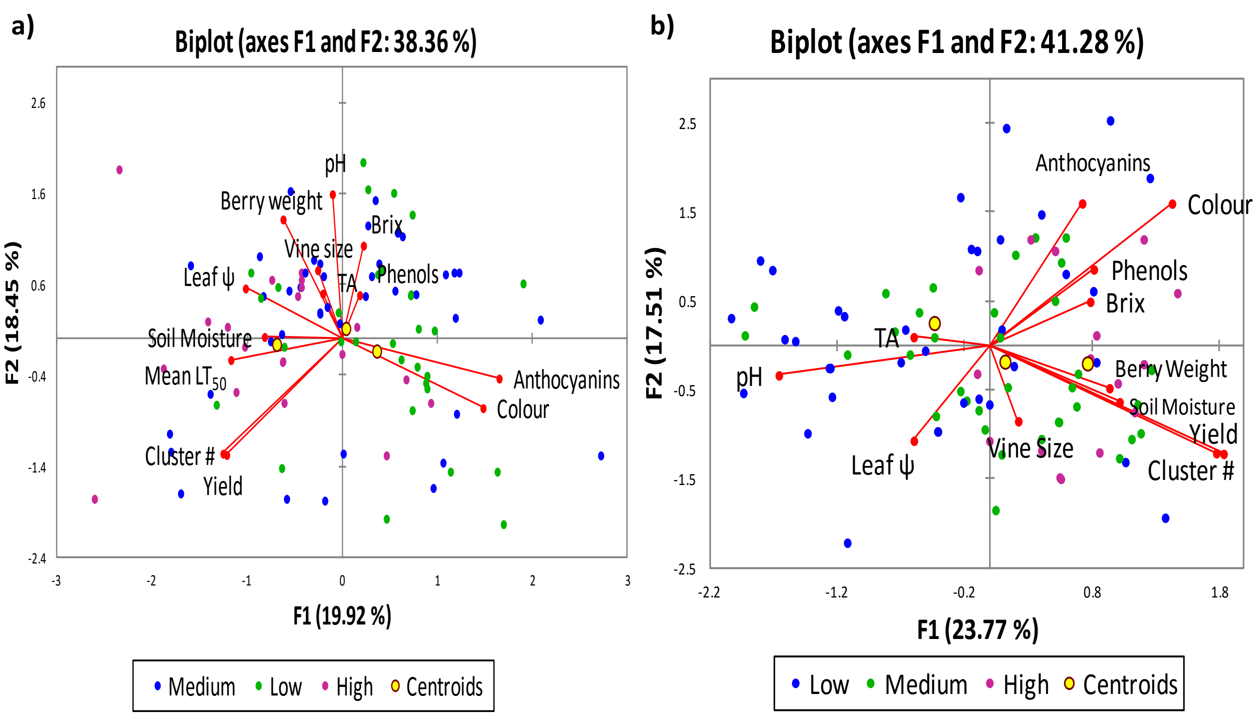

Figure 2.29 Principal component analysis correlation biplot of observations for Coyote's Run Pinot noir (North-South): a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high soil moisture levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

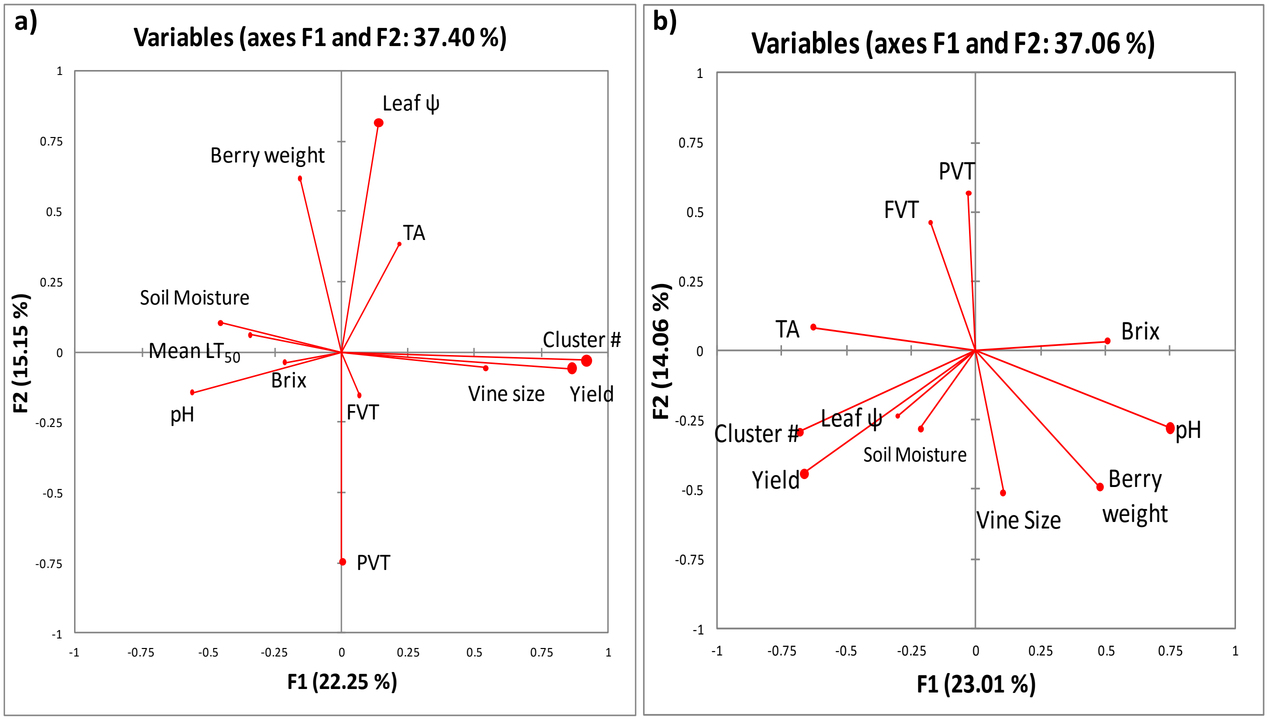

Figure 2.30 Principal component analysis for Cave Spring Riesling: a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and winter hardiness (mean LT_{50}). Abbreviations: TA=Titratable acidity; FVT=free volatile terpenes; PVT=potentially volatile terpenes.

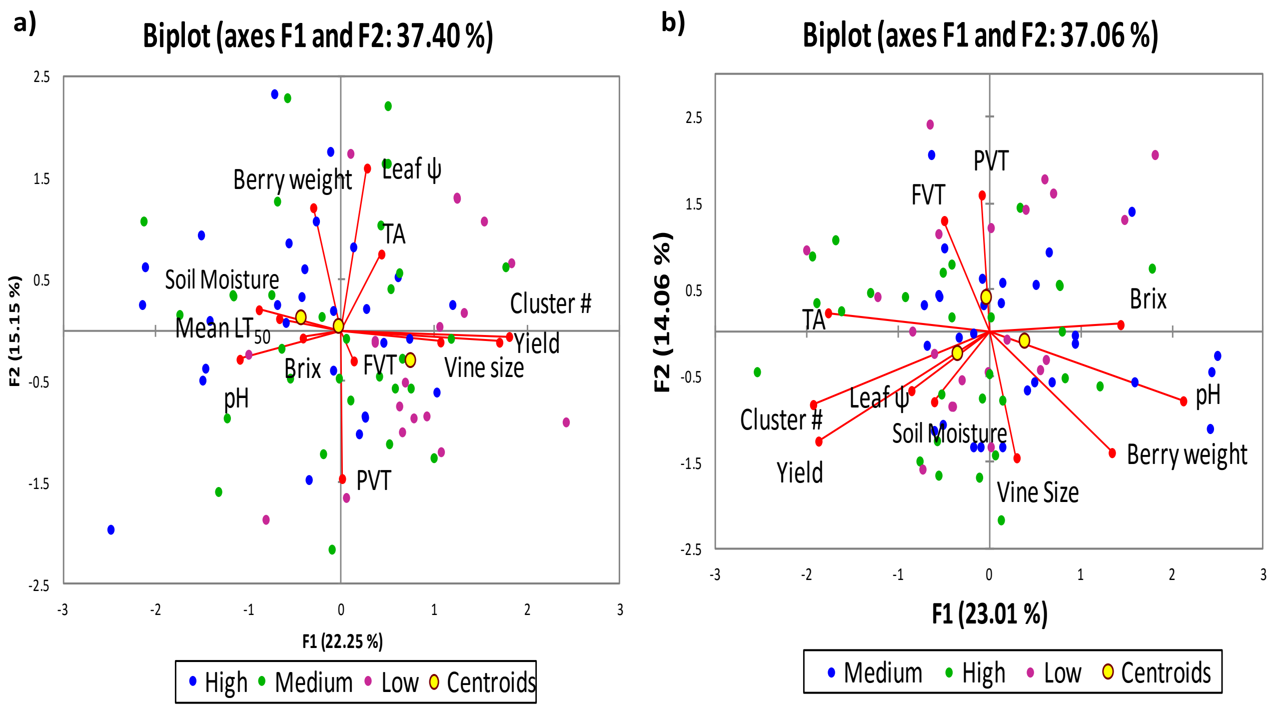

Figure 2.31 Principal component analysis correlation biplot of observations for Cave Spring Riesling: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high soil moisture levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity; FVT=free volatile terpenes; PVT=potentially volatile terpenes.

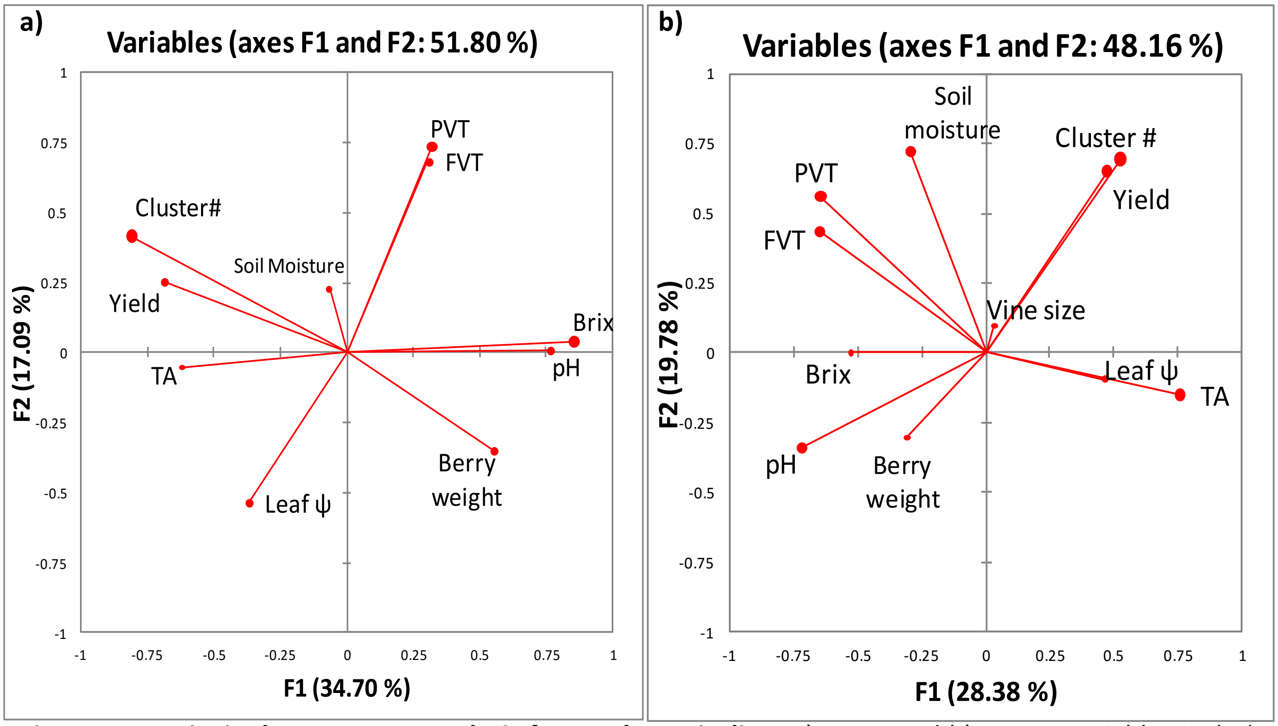

Figure 2.32 Principal component analysis for Lambert Riesling: a) 2014, and b) 2015. Variables include vine water status and berry composition characteristics. No winter hardiness (mean LT_{50}) and vine size data was collected for Lambert Riesling in 2014. Abbreviations: TA=Titratable acidity; FVT=free volatile terpenes; PVT=potentially volatile terpenes.

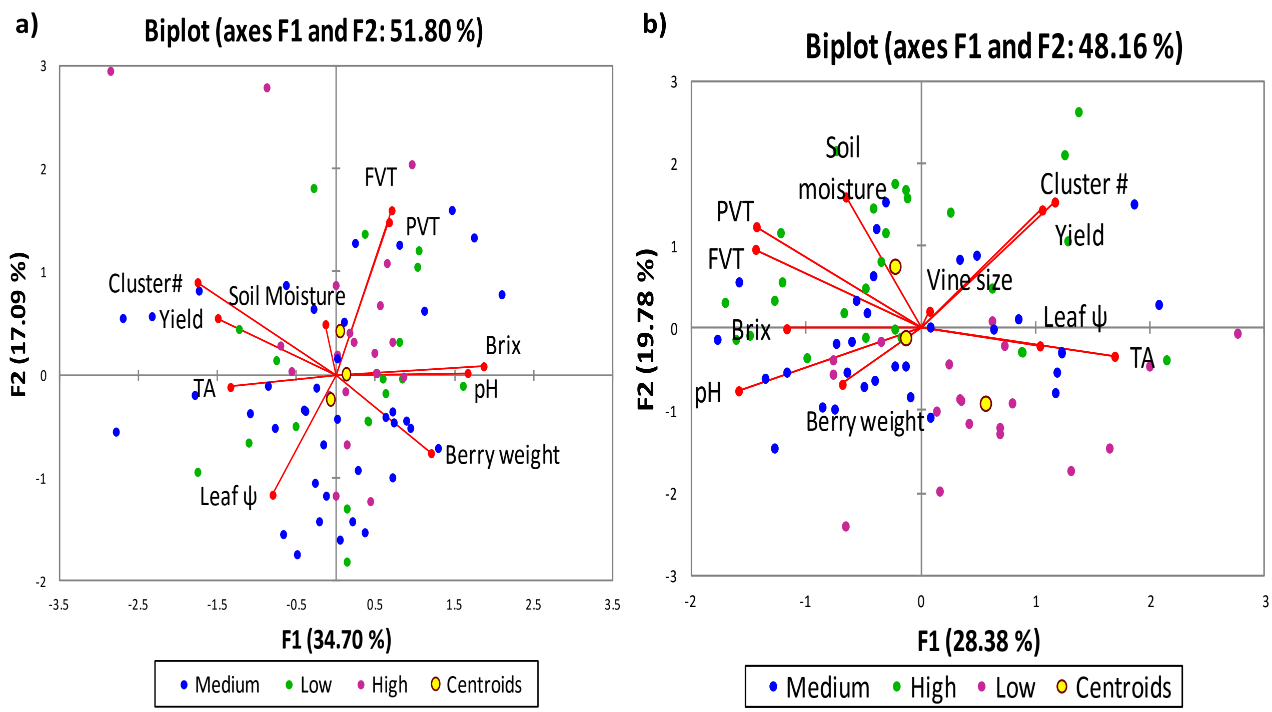

Figure 2.33 Principal component analysis correlation biplot of observations for Lambert Riesling: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high soil moisture levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity; FVT=free volatile terpenes; PVT=potentially volatile terpenes.

CHAPTER 3 : PROXIMAL SENSING TECHNOLOGY AND THE RELATIONSHIP TO VINEYARD CHARACTERISTICS

3.1 ABSTRACT

Proximal sensing technology was developed to overcome many of the restrictions related to satellite -or aircraft- based remote sensing systems. Ground-based proximal sensing systems collect multispectral images in the visible and Near Infrared (NIR) wavebands and they calculate vegetation indices, such as the Normalized Difference Vegetation Index (NDVI). The objective of this study was to assess the usefulness of NDVI measurements acquired by the GreenSeeker™ optical sensor technology in viticulture and relate those measurements with grapevine physiological indicators. It was hypothesized that variability in vegetative expression, yield and plant water status will relate to NDVIs, and that differences in grape quality, phenolics and colour would be identified. It was also hypothesized that spatial variability in the study plots would exhibit a temporally stable pattern. The obtained results suggest that NDVI successfully established relationships with the variables examined; positive relationships were exhibited with vine size, and yield components, while inverse correlations were demonstrated with phenolics in red cultivars, and monoterpenes in Riesling. Regardless of the statistical method employed, the results are considered satisfactory with respect to illustrating the nature of the relationships, alongside the maps produced for all the variables. Clustering patterns in NDVI were confirmed by *k*-means clustering analysis and Moran's *I* spatial autocorrelation index. The usefulness of GreenSeeker™ proximal sensing tool was confirmed, and was indicative of future applicability of this technology to divide vineyards into sub-blocks of different productivity, which will benefit the industry and the consumers alike.

Key words: Precision viticulture, proximal sensing technology, NDVI, spatial variability, temporal stability, zonal management, phenolics, monoterpenes

3.2 INTRODUCTION

Grapevine water status greatly influences berry composition characteristics and harvest quality by affecting canopy and grape growth, yield, and fruit metabolism (Ojeda et al. 2002; Seguin 1986; van Leeuwen & Seguin 2006). Therefore, it is important to monitor the temporal and spatial variability of vine water status in order to manage vineyard operations accordingly (Acevedo-Opazo et al. 2010b). The latter is particularly essential, when regulated deficit irrigation (RDI) practices are implemented (Acevedo-Opazo et al. 2008b, 2010a; Ojeda et al. 2002), since water availability optimisation, especially during the important vine phenological stages (such as budburst, flowering and veraison), can then be targeted through irrigation management (Acevedo-Opazo et al. 2013). Plant water status assessment is a manual technique requiring pressure chambers and nitrogen gases, along with skills in acquiring the data (Ojeda et al. 2002); hence, spatial prediction models were developed to overcome these difficulties (Acevedo-Opazo et al. 2010b, 2013).

Implementation of the "Precision Viticulture" approach requires the involvement of geospatial technologies, such as global positioning system (GPS), and geographical information system software (GIS) (Bramley et al. 2003). Remote sensing and proximal sensing technologies focus predominantly on the vegetative structure, shape and health of the grapevine canopy. The rationale behind this approach is that canopy characteristics project the incorporated influences from grapevines' biophysical environment, which include the climate, soil, disease and pest pressure (Bramley 2010). Normalized Difference Vegetation Index (NDVI) is computed by acquisition of near-infrared (NIR) and red energy measurements from remote-sensing devices. NDVI is calculated by the following formula:

$$NDVI = \frac{NIR - red}{NIR + red}$$

Healthy vegetation will reflect strongly the near-infrared energy and absorb the red portions of the electromagnetic spectrum (EMS), whereas water-, disease- or pest- stressed canopies reflect more red energy (Shellito 2014). NDVI maps were used to evaluate the condition of grapevine canopies (Hall et al. 2002), while NDVI maps from high-spatial resolution imagery were converted to vine leaf area index (LAI) maps to detect canopy variability (Johnson et al. 2003).

When NDVI maps were used to delineate vineyard water restriction zones, vigour was correlated with soil water availability, and plant water status was a major factor impacting vigour, yield and quality (Acevedo-Opazo et al. 2008a). Indeed, the NDVI measurement is the observation of photosynthetically active biomass (PAB). As a result, NDVI shows strong correlations with vine size and is indicative of health or absence of stress in grapevines (Bramley 2010). Utilisation of remote sensing as a means of predicting fruit quality has been explored with the strongest negative correlations between quality attributes in red grapes (i.e., phenolics and anthocyanins) and canopy NDVI occurring at the time of veraison (Hall et al. 2011; Lamb et al. 2004; Martinez-Casasnovas et al. 2012).

Technological research has also been focused on developing rapid methods for the direct assessment of plant water status using high spatial resolution sensors. Infrared thermography is quite promising for detecting plant stress from indirectly measuring stomatal conductance (Jones et al. 2002; Stoll & Jones 2007). Satellite or airborne-based technologies are tedious in nature, as they are implicated with technical obstacles, such as vineyard grass cover or cloud cover, and involve high operating costs (Acevedo-Opazo et al. 2008a). Yet promising results were demonstrated in a recent study about assessing soil moisture using thermal remote sensing images obtained over a vineyard grass-covered soil in the Niagara Region in Ontario (Soliman et al. 2013).

Strong, positive correlations among airborne spectral reflectance imagery and prediction of pruning weights were demonstrated in two vintages (Dobrowski et al. 2003). Similarly, consistent relationships over time between pruning weights and NDVI were obtained using a ground-based sensor in Merlot vineyards in northern Greece (Stamatiadis et al. 2006). Vine productivity in terms of yield was also predicted by active canopy reflectance sensors measuring NDVI in vineyards planted with cvs. Cabernet Sauvignon and Xinomavro (*Vitis vinifera* L.) (Taskos et al. 2013).

Generally, proximal sensing systems collect multispectral images in visible wavebands (green or red) and in the NIR, calculating thereafter vegetation indices and making inferences about crop growth (Mazzetto et al. 2011). Vegetative indices can be determined in real-time by active optical ground sensing devices, such as the GreenSeeker™ RT100 (N-Tech Industries Inc., Ukiah, CA). The GreenSeeker™ is a ground-based apparatus developed by N-Tech Industries (Ukiah, CA) and the Oklahoma State University (Stillwater, OK), to calculate NDVIs from reflectance measurements (Drissi et al. 2009). Much research has been mainly focused on the GreenSeeker™ application in cotton, wheat and rice (Inman et al. 2007), but limited publications about its applicability in viticulture exist, and these studies are predominantly concentrated on characterising the spatial distribution of vine vegetation (Drissi et al. 2009).

Proximal sensing monitoring tools were initially developed to overcome remote sensing limitations associated with canopy architecture, inter-row spacing and shadows, weather, and masking of non-vine pixels (Ledderhof et al. 2015; Mazzetto et al. 2011; Stamatiadis et al. 2006). The GreenSeeker™, ground-based proximal sensing device utilised in this project, scans the entire canopy laterally (Drissi et al. 2009), and automatically reports the NDVI values. Given the vertically shoot positioned canopies in most commercial vineyards today, these active optical sensors (with their own light source) can acquire much information about the canopy without distractions by background interferences, such as soil-cover (Stamatiadis et al. 2010).

The objective of this study was to assess the usefulness of NDVI measurements acquired by the GreenSeeker™ proximal sensing technology with grapevine physiological indicators. More specifically, it was hypothesized that variability in vegetative expression, yield and plant water status will relate to NDVIs. It was also anticipated that NDVIs would correlate with differences in grape composition, including phenolics and monoterpenes. Grapevine canopies with environmental biophysical restrictions, such as low soil water availability, are expected to reflect less light and thus show a smaller NDVI value than larger, healthier and well-watered canopies. Vine vigour (estimated by pruning weights or vine size) was predicted to be a key factor with NDVI variability. Proximal sensing technology and NDVI, was expected to be an evaluation tool for observing the spatial variability of grapevine production.

3.3 MATERIALS AND METHODS

3.3.1 VINEYARD PLOTS SELECTION, FIELD PROCEDURES & CHEMICAL ANALYSIS

Three commercial vineyards in the Niagara Peninsula, Ontario, containing large blocks of *V. vinifera* were selected, and included two blocks each of Cabernet franc, Riesling and Pinot noir (Figure A 1). Approximately 85 healthy and representative vines were chosen per vineyard block, 20 of which were selected for leaf ψ measurements, bud LT_{50} bud survival and monoterpene analysis. Sites were geolocated with the use of advanced Global Positioning System technology (GPS) using an Invicta 115 GPS Receiver (Raven Industries, Sioux Falls, SD) with 1.0 to 1.4 m accuracy and the grape vines were marked in a geo-location grid. Post collection differential correction was conducted using the Port Weller, Ontario base station correction to final accuracy of ≈ 30-50 cm. Field measurements and grape samples for berry composition chemical analysis were obtained from all these vines during the 2014 and 2015 growing seasons at berry set, lag phase, and veraison. Soil water content, vine water status measurements and viticultural data collection were conducted according to Willwerth et al. (2015), berry composition analysis for Cabernet franc and Pinot noir as in Hakimi Rezaei & Reynolds (2010), and monoterpenes analysis for Riesling as in Reynolds et al. (2010). All methods used are described in detail in *Chapter 2*.

3.3.2 GREENSEEKER™ TECHNOLOGY

The monitoring system used in this study consisted of two paired GreenSeeker™ sensors, and a high-performance DGPS double frequency receiver with real-time kinematic correction (AgGPS® 162, Trimble Navigation, Englewood, CO). The GreenSeeker™ active optical sensor technology uses electroluminescent diodes (LED) to generate high intensity light at the 660 ± 10 nm (Red) and 770 ± 15 nm (NIR) wavebands. The LEDs are pulsed at 100 Hz, have a 60 cm-wide measuring pattern (61x10 mm) and a 0.01-0.12 m discrepancy (Mazzetto et al. 2010). Each sensor receives 100 measurements per second (GreenSeeker™ 2015). The beams use horizontal as well as vertical footprints, with a 60-cm field of view, as a means of scanning the entire canopy area.

The GreenSeeker™ unit (Trimble Navigation, Englewood, CO) is mounted on a metal frame on a four-wheel-drive vehicle and collects geo-referenced data, while travelling in the vineyard rows (Figure 3.25). Electronic filters allow for background reflections removal, while the driving direction of the vehicle had been previously proven negligible (Mazzetto et al. 2010). GreenSeeker™ computes NDVI values in real-time and the files acquired were stored as NDVI data points in shapefile formats (.shp), which could thereafter be imported to the GIS computer software ArcGIS 10.3 (Environmental Systems Research Institute (ESRI) Redlands, CA). Dates close to soil moisture and leaf ψ data collection were selected for NDVI measurements, over three times during the growing season.

When combined with DGPS, active ground sensors can provide real-time data of high spatial resolution, based on which the vineyard management can be streamed to even vine-by-vine basis (Stamatiadis et al. 2006). As an active proximal sensor, GreenSeeker™ possesses its own source of light; the advanced electronic and optical systems are able to differentiate between natural light and modulated (pulsed) light, which overcomes data collection issues regarding the time of day, cloud cover, and effect of shadows (Stamatiadis et al. 2009, 2010). While NDVI can take numbers between -1 and +1, objects of agricultural relevance have only positive values, and more specifically intensely vegetated ones take NDVI values ≈1 (Lamb 2000). In this study, a threshold value of 0.60 was chosen for the NDVI maps production in order to highlight the small differences in vineyard vegetative growth; the proposed threshold value is in agreement with the literature (Calcante et al. 2012; Mazzetto et al. 2010, 2011).

3.3.3 STATISTICAL ANALYSIS

Data analysis was performed on all variables using XLStat-Pro statistical software (2015 version, Addinsoft, New York, NY). Initially, all variables were carefully inspected for normality and errors. Pearson's correlation tests were performed to examine the strength of linear relationships among NDVI measurements, yield components, and berry composition variables. Principal component analysis (PCA) was used to illustrate relationships among the variables. Plotted points in PCA were resized based on their $\cos^2$ values in order to confirm whether the variables were well linked to the axes. The non-hierarchical classification algorithm *k*-means was conducted for three clusters of low, medium and high NDVI, and supplemented the PCA as a qualitative variable. Statistical procedures were carried out as described in *Chapter 2*.

Additionally, tables containing summarised statistics for all variables measured across all vineyard sites in both vintages (2014-2015) were produced (Tables A4-A9). The coefficient of variation (CV %) is a meaningful index of gross variation, but as proposed in Bramley (2005) and later adopted by other studies (Scarlett et al. 2014), the variable "spread" was also calculated. "Spread" is defined as the range among the maximum and minimum values of an attribute expressed as a percentage of the median. "Spread" essentially relays some of the information provided by a "box plot" and it is a theoretically better indicator of the range of variation among variables and vintages, which can be more easily interpreted by winemakers.

Furthermore, multiple regression analysis was performed to evaluate which variables predict or influence the variable of interest (dependent variable = NDVI) (Calcante et al. 2012). In conjunction with significance tests, multiple regression models were used to assess whether the entire set of predictor variables can significantly predict the NDVI (Warner 2008). It is important to have a rationale for the inclusion of variables in the prediction model, which has to be based on well-studied literature, in order to be able to suggest a "causal influence" on the NDVI, and of course take into account the predictive usefulness of the variables (Warner 2008).

In comparison with the hierarchical (or sequential) regression and the statistical (or data-driven) regression, the direct or simultaneous regression (i.e., a regression analysis in which all variables are entered in one step) was selected for this study (the option "best model" was chosen, confidence interval 95%). In this type of regression, all variables are given an equal treatment, which allows for the predictive usefulness of each variable to be assessed against all the other variables (Warner 2008). For a multiple regression to have "meaningful" results, the ratio of number of observations to number of predictor variables has to follow a rule; here the maximum number of predictor variables was set at maximum 5, based on the assumption of a medium-size relationship between criterion and predictors ($N \geq 50 + 8*m$, where (N) is the number of observations and (m) is the number of predictors) (Green 1991).

3.3.4 MAPPING PROCEDURES

Global Positioning System (GPS) technology is a satellite-based navigation system, and differential GPS techniques provide accuracy to the centimeter level, predominantly employed at high precision tasks such as crop mapping (Matese & Di Gennaro 2015). For all mapping procedures, the GIS software ArcGIS 10.3 (Environmental Systems Research Institute (ESRI) Redlands, CA) was used. Mapping techniques were performed as described in *Chapter 2* for the variable NDVI.

Spatial autocorrelation is an important tool used in geographical analysis to demonstrate that values of a variable are related (in most cases positively) with their neighbouring points, based on Tobler's first law of geography that "everything is related to everything else, but near things are more related than distant things" (Griffifth 2009). One of the most commonly used measurements of spatial autocorrelation is Moran's index (Moran's *I*), which stems from Pearson's correlation coefficient and has the critical value of I_t=0 (Chen 2013). Moran's *I* values can be found in the Appendix for all vineyard sites and vintages (Tables A22-A27).

3.4 RESULTS

NDVI measurements were analysed against yield components, vine water status measurements (leaf ψ and soil moisture) along with berry composition and bud survival data. Probability (*p*-value) tables are provided for all sites and all vintages in the Appendix (Tables A10-A21). In those cases that significant relationships among NDVI and grapevine variables were identified, scatter plots were created. The 2015 LT_{50} results did not show any significant correlations and thus, were not included in the subsequent data analysis. PCA and multiple regression models were conducted for the means of NDVI, leaf ψ, soil moisture, and LT_{50}. Observation biplots are displayed in different colours after being subjected to *k*-means clustering of low, medium and high NDVI.

Summarised statistics of the variables are provided in the Appendix (Tables A4-A9); the most notable coefficient of variation (and consequently spread) was observed for yield ranging from 23.5% to 62.8% across sites and years (in partial agreement with Taskos et al. (2014); CV % 26.7-46.2), further supported by high variability in vine size (CV% 22.9-38.9). The latter statement is indicative of the potential of a PV approach for zonal management and/or selective harvesting (Bramley & Hamilton 2004). Likewise, variables associated with the yield exhibit similar intra-field variation, but in a smaller extent than yield, with the exception of cluster number at Lambert Riesling in both years (Table A9). With respect to berry composition metrics, the most variability was exhibited with anthocyanins, colour and phenols as in Martinez-Casasnovas et al. (2012), and monoterpenes. In this work, variability in anthocyanins ranged from 12.29% to 24.96%, in agreement with other studies; in Coonawarra cool climate region anthocyanins ranged from 13.7-21.6% (Bramley 2005; Bramley & Lamb 2003) and in Cabernet Sauvignon from 15.7-32.4% (Taskos et al. 2014). Monoterpenes had values between 15.5-30%. Lastly, NDVI demonstrated the least variability across sites and years, from 0.84-6.40%, comparable only with pH, and in disagreement with Martinez-Casasnovas et al. (2012) whose NDVI CV% values ranged from 13.1-19%, probably attributed to image acquisition method (GreenSeeker™ vs. satellite).

3.4.1 PEARSON'S CORRELATION RESULTS

Pearson's correlation tables for NDVI and significance levels are summarised in Table 3.2.

i. *NDVI vs. Yield components*

NDVI was correlated with cluster number in Pinot noir North-South (both years positively; Figures 3.1-3.2) and in Lambert Riesling 2014 (negatively; Figure 3.3) and with yield in Pinot noir North-South 2014 (positively; Figure 3.1) and in Lambert Riesling 2014 (negatively; Figure 3.3). Cluster weight was positively correlated with NDVI in Cave Spring Cabernet franc (both years; Figures 3.4- 3.5). Vine size correlated positively with NDVI in Cave Spring Cabernet franc (both years; Figures 3.4-3.5), in Pinot noir North-South 2015 (Figure 3.2) and in Cave Spring Riesling 2015 (Figure 3.6).

ii. NDVI vs. Soil moisture and leaf ψ

NDVI associated positively with SM July in Pinot noir North-South (both years; Figure 3.1), with SM August in Pinot noir North-South 2015, with SM September in Pinot noir East-West 2014 (Figure 3.7). Mean SM was positively correlated with NDVI in Cave Spring Cabernet franc (both years; Figures 3.4-3.5) and in Pinot noir North-South 2015 (Figure 3.2). In Lambert Riesling 2015, all three SM measurements were negatively correlated with NDVI (Figure 3.8).

NDVI exhibited highly inconsistent relationships with leaf ψ throughout the growing season; leaf ψ July was correlated in Lambert Riesling 2014, Pinot noir East-West 2014 and in Lambert Cabernet franc 2015 (negatively; Figures 3.3, 3.7 and 3.10 respectively) and in Pinot noir East West 2015 (positively; p=0.000, data not shown). Leaf ψ August correlated negatively with NDVI in Lambert Cabernet franc 2014 (Figure 3.11) and in Lambert Riesling 2015, and positively in Pinot noir East-West 2015 (p=0.011, data not shown). Leaf ψ September was positively correlated with NDVI in Lambert Cabernet franc 2015 and negatively in Cave Spring Cabernet franc 2015 (data not shown). Lastly, mean leaf ψ was negatively correlated with NDVI in Lambert Riesling 2014 and Cave Spring Cabernet franc 2015 (Figures 3.3,3.5) and in Pinot noir East-West 2015 positively (Figure 3.9).

iii. NDVI vs. berry composition

NDVI demonstrated few relationships with berry composition variables. NDVI correlated with Brix in Lambert Cabernet franc 2014 (positively; Figure 3.11), in Lambert Riesling 2014 and in Cave Spring Cabernet franc 2014 (negatively; Figures 3.3-3.4). Relationships with pH were negative in nature in Cave Spring Cabernet franc 2014 and Pinot noir East-West 2014 (Figures 3.4, 3.7), while in Lambert Riesling 2014 and Lambert Cabernet franc 2015 were positive

(Figures 3.3, 3.10). Titratable acidity was positive associated with NDVI only in Lambert Cabernet franc 2014 (Figure 3.11).

iv. NDVI vs. secondary metabolites

Secondary metabolites in red varieties demonstrated inverse relationships with NDVI; anthocyanins in Cave Spring Cabernet franc 2014 and Pinot noir East-West 2014 (Figures 3.4, 3.7), colour in Cave Spring Cabernet franc 2014 and Lambert Cabernet franc 2015 (Figures 3.4, 3.10) and phenols in Cave Spring Cabernet franc 2014 and Lambert Cabernet franc 2014 (Figures 3.4, 3.11). In Riesling, inverse relationships were exhibited among FVTs and NDVI in all blocks (Figures 3.6, 3.8, 3.12), except for Lambert Riesling 2014 whereby terpenes (FVTs and PVTs) were positively associated with NDVI (Figure 3.3).

In summary, NDVI revealed consistently positive relationships with yield components and vine size over the two years of study (six of 12 blocks across two seasons); for instance, vine size was positively correlated with all NDVI measurements in Cave Spring Cabernet franc 2015. With regard to vine water status different relationships were exhibited between soil moisture or leaf ψ and NDVI. More specifically in red cultivars, soil moisture had a positive influence on NDVI (five of eight blocks), as in Pinot noir East-West 2015 (SM July, August and mean; Figure 3.9), whereas patterns with leaf ψ were dispersed and often negative in nature (four of eight blocks), as in Cave Spring Cabernet franc 2015 (leaf ψ September, mean leaf ψ; Figure 3.5). Vine water status in Riesling (soil moisture and leaf ψ) displayed a negative influence on NDVI (exhibited only in Lambert vineyard, no effect in Cave Spring). Anthocyanins, colour and phenols were negatively correlated with NDVI (four of eight blocks). Inverse correlations were profound among NDVI measurements early in the season, such as between NDVI July and anthocyanins, colour and phenols, as in Pinot noir North-South 2015 ($p=0.020$, 0.009, and 0.023, respectively, data not shown). In Riesling, NDVI demonstrated strong negative relationships only with FVT (three of four blocks) and positive correlations with the terpenes in Lambert Riesling 2014 (Table 3.2). Overall, the vineyards exhibited representative examples of relationships with NDVI were: the Cave Spring Cabernet franc 2014, where many important relationships were revealed among NDVI and important berry composition variables (Brix, pH, anthocyanins, colour and phenols), vine size, cluster weight and mean soil moisture (Figure 3.4), as well as the Lambert Riesling 2014 with Brix, pH, FVT and PVT (positively), along with yield, cluster number, and leaf ψ (July, mean) (negatively; Figure 3.3).

3.4.2 LINEAR REGRESSION MODEL RESULTS

Regression models for all vineyard sites and for both vintages are summarised in Table 3.1. Overall, significant models ($p<0.05$) for NDVI were produced for all vineyards, with yield components, leaf ψ, soil moisture and vine size contained as variables in some models (seven, six, and four of 12 blocks, and five of 11 blocks, respectively). Berry composition variables appeared in five of eight red cultivar sites and in three of four Riesling sites.

3.4.3 PRINCIPAL COMPONENT ANALYSIS RESULTS

i. Cabernet franc

Principal component analysis (PCA) in 2014 Lambert Cabernet franc explained 34% of the variability in the dataset in the first two PCs (Figure 3.13a). Cluster number, anthocyanins and colour were closely correlated (PC1), while yield and berry weight were inversely correlated with Brix and phenols (PC2). NDVI was closely related to leaf ψ and vine size, while *k*-means clustering for NDVI did not exhibit any apparent patterns (Figure 3.14a). In 2015, PCA accounted for 40.64% of the variability in the first two PCs; cluster number, yield, vine size and

TA were inversely correlated to pH, and anthocyanins, colour, and phenols closely related (Figure 3.13b). Although NDVI was not a variable important to the total variability of the dataset, *k*-means clustering indicated that high NDVI observations were located closer to NDVI and soil moisture (Figure 3.14b).

PCA in 2014 Cave Spring Cabernet franc explained 45.03% of the variability in the first two PCs; NDVI was strongly related with vine size, soil moisture and TA and inversely correlated with Brix, pH, anthocyanins, colour and phenols (PC1), while yield and cluster number were inversely correlated with leaf ψ (PC2) (Figure 3.15a). Distinct clustering was demonstrated with *k*-means analysis; observations of low NDVI appeared close to anthocyanins, colour, phenols and pH, while the ones with high NDVI with yield, cluster number and vine size (Figure 3.16a). In 2015, PCA accounted for 37.38% of the variability in the first two PCs; anthocyanins, colour, phenols and Brix were closely related (PC1), while NDVI, cluster number, yield and vine size were inversely correlated with soil moisture and leaf ψ (PC2) (Figure 3.15b). Similarly with the 2014 vintage, *k*-means clustering revealed that observations with low NDVI were located close to anthocyanins, colour, phenols and Brix, and high NDVI was ones were closer NDVI, yield, and vine size variables (Figure 3.16b).

ii. Pinot noir

At Coyote's Run Pinot noir East-West block 2014, PCA explained 37.87% of the variability in the first two PCs; cluster number, yield, berry weight and vine size were inversely correlated with soil moisture (PC1), while NDVI and Brix were found negatively related to pH, TA, colour and phenols (Figure 3.17a). Observations of high NDVI appeared closer to soil moisture and the lower NDVI ones closer to anthocyanins, colour, and berry weight (Figure 3.18a). In 2015, PCA explained 43.35% of the variability in the first two PCs; NDVI, berry weight, leaf ψ and vine size were inversely correlated with anthocyanins, colour, phenols and Brix (PC1), while cluster number, yield and pH were inversely correlated with TA and soil moisture (PC2) (Figure 3.17b). K-means clustering did not show any patterns, however a clear domination of high NDVI observations was noted (65 of 84 observations belonged in the high cluster) (Figure 3.18b).

At Coyote's Run Pinot noir North-South block 2014, PCA explained 35.89% of the variability in the first two PCs; cluster number and yield were inversely correlated with anthocyanins and colour (PC1), berry weight was closely related to pH (PC2) and NDVI was found closely related with soil moisture, leaf ψ and LT_{50} (Figure 3.19a). Supplementing the PCA with *k*-means clustering did not reveal any patterns in the dataset (Figure 3.20a). In 2015, PCA accounted for 39.72% of the variability in the dataset in the first two PCs; cluster number, yield, berry weight and soil moisture were inversely correlated with pH and TA (PC1), while NDVI, vine size and leaf ψ were inversely correlated with anthocyanins, colour and phenols (PC2) (Figure 3.19b). Observations of high NDVI appeared closer to soil moisture, yield and berry weight, whereas low NDVI was associated with berry composition variables (Figure 3.20b).

iii. Riesling

In Cave Spring Riesling 2014, PCA explained 34.89% of the variability in the dataset in the first two PCs; cluster number, yield, vine size related to pH (negatively in PC1), while NDVI, berry weight and leaf ψ were inversely correlated with FVT and PVT (PC2) (Figure 3.21a). *K*-means clustering demonstrated that low NDVI associated with FVT and PVT, and high NDVI with berry weight, NDVI and leaf ψ (Figure 3.22a). In 2015, PCA accounted for 35% of the variability in the first two PCs; cluster number, yield and TA were inversely correlated with berry weight, Brix and pH (PC1), while NDVI, vine size were inversely correlated with FVT and PVT (PC2) (Figure 3.21b). Similarly with the 2014 vintage, *k*-means revealed clustering of the low NDVI observations with FVT and PVT, while the high NDVI ones appeared close to yield and vine size (Figure 3.22b).

PCA at Lambert Riesling 2014 accounted for 50.49% of the variability in the dataset in the first two PCs; yield, cluster number and TA were inversely correlated with berry weight, pH, and Brix (PC1), while the NDVI was related to FVT and PVT (PC2) (Figure 3.23a). Unexpected patterns were exhibited by *k*-means with high NDVI associated with FVT and PVT (Figure 3.24a). In 2015, PCA explained 45.46% of the variability in the first two PCs; leaf ψ and TA were inversely correlated with FVT, PVT, Brix and pH (PC1), while NDVI and berry weight were inversely correlated with soil moisture, yield and cluster number (PC2) (Figure 3.23b). *K*-means clustering revealed that low NDVI observations appeared closer to FVT, PVT and soil moisture, whereas the high NDVI ones were closer to berry weight, NDVI and TA (Figure 3.24b).

In summary, PCA indicated that NDVI established relationships in seven of eight red cultivar blocks and in all four Riesling blocks across two vintages. More specifically, positive relationships were exhibited with vine size, vine water status, and yield components (six, five, and four of 11 blocks, respectively). Lastly, NDVI was inversely correlated with phenolics in red wine grapes (four of seven blocks), while it correlated with FVT and PVT for Riesling (negatively in two, and positively in one of four blocks).

In general, PCA was in agreement with correlations and regressions, which is indicative of the strong relationships among the variables reported here. When comparing linear correlations, regression models, and PCAs, high NDVI was associated with yield components and vine size, while low NDVI was associated with higher anthocyanins, phenols and colour, with *k*-means clustering confirming the latter (four of seven blocks). Similar negative relationships were demonstrated for terpenes with *k*-means clustering verifying the patterns (in three of four blocks, while in one block NDVI was positively correlated with terpenes). Vine water status was another important variable influencing NDVI with inconsistent patterns - positive effect in most cases for red cultivars and negative for Riesling. Overall, the statistical methods were adequate to ascertain the nature of relationships among NDVI and all the other variables.

3.4.4 MORAN'S *I* INDEX

Moran's *I* Indices indicated a somewhat clustered pattern (mean clustering incidence ≈66%) among the NDVI measurements across all vineyard sites and vintages (Tables A22-A27). More specifically, at Coyote's Run the East-West block showed only 50% clustering incidence, whereas the North-South >80%. Likewise, at Cave Spring the Cabernet franc block revealed >80% clustering incidence, but the Riesling block only ≈33%. Lastly, the Lambert Cabernet franc exhibited 50% clustering incidence, and the Riesling block 100%.

3.4.5 MAP ANALYSIS

i. Spatial Analysis of Lambert Cabernet franc

Soil moisture showed consistent patterns in both vintages, whereby the North side had low values and the South (South-East) had high (Figure A3). NDVI (Figure A 15) correlated well with berry weight (2015) (Figure A 21), with Brix, TA (2014) and pH (2015) (Figure A 27), somewhat with leaf ψ (Figure A 9), and with phenols (2014) along with colour and anthocyanins (Figure A 33). All berry quality variables showed very high temporal consistency in both years and were inversely correlated with soil moisture.

ii. *Spatial Analysis of Cave Spring Cabernet franc*

High soil moisture showed temporally consistent patterns on the East side of the block (in 2014), and low values in 2015 (Figure A 4). Similarly, the east side was followed by high leaf ψ values in 2014, and low leaf ψ was found in 2015 for the central and eastern side (particularly depicted by the September and mean map) (Figure A 10). NDVI (2014) Figure A 16) was highly correlated with soil moisture (2014) and somehow with cluster weight (2014), while NDVI (2015) showed inverse patterns with SM (2015), but highly similar patterns with vine size (2015) (Figure A 22). Soil moisture associated well with berry weight (2014), and yield (2015). Brix, pH and TA (2014) were correlated with vine size (2014) and somewhat to NDVI (2014), while in 2015 Brix showed similarities in the lower south-east side of the block with berry composition variables (2015) (Figure A 28). Berry composition variables (anthocyanins, colour and phenols) showed very high temporal consistency in both years, and were inversely correlated with NDVI 2014 (Figure A 34).

iii. *Spatial Analysis of Coyote's Run Pinot noir East-West*

Soil moisture showed highly temporally consistent patterns in both years, with high SM in the eastern side, and low SM in the western side of the block (Figure A 5). Leaf ψ showed inconsistent patterns in 2014, while in 2015 higher values were found in the eastern side- in correlation with soil moisture (Figure A 11). NDVI (Figure A 17) exhibited correlations with yield components (yield, berry weight, cluster weight and vine size) in both years (Figure A 23), TA (2014) and pH (2015) (Figure A 29), and dispersed relationships with berry quality variables. Anthocyanins and colour (2014) correlated well with SM (Figure A 35).

iv. Spatial Analysis of Coyote's Run Pinot noir North-South

Soil moisture showed very consistent patterns in both years, with high SM in the west-north west side, and low SM in the south-south east side of the block (Figure A 6). Leaf ψ did not show any particular patterns, except for September 2015 which was correlated with soil moisture September 2015 (Figure A 12). NDVI established correlations with yield (2014), somewhat with pH (2014) and opposite with vine size (2014) (Figure A 18). Likewise, NDVI (2015) showed similarities with yield (2015) and vine size (2015) (Figure A 24), while similarities with soil moisture (2015) were very profound. Vine size showed many similarities with TA in 2014 (Figure A 30). Unexpected positive relationships were found among berry composition variables and NDVI in 2014; whereas in 2015 inverse relationships were exhibited for phenols and colour with NDVI (2015) (Figure A 36).

v. Spatial Analysis of Cave Spring Riesling

Low soil moisture pockets were found in the South side of the Riesling block consistently across the seasons, along with the north-west corner in September of both years (Figure A 7). Leaf ψ in September (2014 and 2015) corresponded with soil moisture September measurements (Figure A 13). NDVI (Figure A 19) correlated well with yield (2014 and 2015), berry weight (2014), cluster weight (2015) and vine size (2014) (Figure A 25), as well as TA (2015) and terpenes (FVT) (Figure A 37). Vine size correlated with yield (in 2014) and pH (in 2015) (Figure A 31).

vi. Spatial Analysis of Lambert Riesling

Soil moisture exhibited very temporally consistent patterns in both years, with north-west side and south-east having low values, while the centre of the block (east) showed high values (Figure A 8). Similarly, NDVI showed very temporally consistent patterns (Figure A 20), and established correlations with Brix (2014), pH (2014) and TA (2015) (Figure A 32). Moreover, NDVI showed inverse relationships with yield, soil moisture and terpenes (2015), while positive relationships appeared with berry weight, cluster weight (2015) and terpenes (2014) (Figures A 8, A 26, A 37).

3.5 DISCUSSION

The principal objective of this study was to evaluate the relationship of NDVI measurements acquired by the GreenSeeker™ proximal sensing technology with grapevine physiological indicators. In particular, it was hypothesized that NDVI would establish positive correlations with yield components, vine vigour, and vine water status, which would be further extended to differences in grape composition, particularly phenolics and monoterpenes. Additionally, a second hypothesis was that NDVI would be a satisfactory indicator of vineyard canopy variability, and that those patterns of variability would show temporal stability. Statistical results (correlation tests, PCAs, and multilinear regression models) along with maps produced for all the variables examined here are generally supporting the hypotheses, but not consistently.

With regard to the first hypothesis, NDVI exhibited the anticipated correlations with yield and vine size; however, in some cases relationships were not as strong as others were. It was previously demonstrated that the (remotely-sensed) NDVI is linearly correlated to vertically shoot positioned (VSP) vine biomass (Dobrowski et al. 2002), and that vegetative growth is considered excessive when mean vine size is > 1 kg/m row or 1.3 kg/vine (Dobrowski et al. 2003; Stamatiadis et al. 2006). In this study, all vineyard sites had maximum values of pruning weights well above the suggested value (except for Coyote's Run East-West and Coyote's Run North-South 2014), with subsequent implications in terms of NDVI saturation at high vegetative growth situations (Hall et al. 2008; Stamatiadis et al. 2006). Well-balanced vines, with increased fruit quality efficiency, have a ratio of yield to pruning weight between 4 and 10 in single-canopy trellis systems (Kliewer & Dokoozlian 2005). Vine balance was only demonstrated in six of 11 blocks (data not shown), with all Riesling values falling into the recommended range, and with the red cultivar sites showing different patterns inconsistently between the two vintages. Other authors suggest an even stricter range of 6 to 10, with lower values related to low yields but excessive vine vigour and with values >10 associated with fruit maturity interruptions and grape quality reduction (Jackson 2008). In this case, only two of 11 blocks appeared to be well-balanced, using the stricter range.

Another reason for ambiguous correlations among NDVI and vine size might be the scanning viewing angle; stronger correlations were achieved when the passive sensors scanned the canopy from the top at veraison (Stamatiadis et al. 2006), instead of the lateral positioning, which can actually display a better estimate early in the growing season (Tagarakis et al. 2013). Indeed, NDVI measurements can detect less accurately (due to saturation phenomena) differences in the grapevine biomass as vegetation growth increases. The latter was partially confirmed by our results showing a higher degree of correlations between yield and NDVI measured early in the season as in Tagarakis et al. (2013), in comparison to later in the season (when correlations were often negative in nature; e.g., in Coyote's Run North-South 2015 and Cave Spring Riesling 2015 - data not shown). Cluster number followed generally similar correlation patterns as yield, as in Stamatiadis et al. (2009). Although vine water status was a statistically significant variable, relationships followed irregular patterns and varied across fields and vintages for the red cultivars, and in contrast with Santesteban et al. (2013). Inverse correlations were observed in Riesling, a phenomenon probably attributable to canopy microclimate and environmental constraints.

Regardless of the statistical method employed, a potential anomaly was exhibited in the dataset. In Lambert Riesling 2014 (Table A20, Figure 3.23a, Table 3.1, Table 3.2) many significant correlations were the inverse of what was expected, with NDVI measurements showing negative relationships with yield components (consistent across the season) and positive with berry composition attributes (such as terpenes), as in Marciniak et al. (2013). Negative relationships have been reported in other studies too, and are attributed to NDVI being a direct indicator of changes in canopy microclimate (Cunha et al. 2010). Pruning weights were not obtained for the Lambert Riesling 2014, and therefore vine balance cannot be calculated, yet the spread for the variable yield was much lower in 2014 than in 2015 (a well-balanced year) with mean NDVI spread in 2014 almost double than in 2015 (Table A9), clearly suggesting an off-balance vineyard site.

Despite the fact that demonstration of relationships among NDVI with vine vigour and yield components is necessary for PV applications, the quality of the final product (i.e. wine) and its subsequent value, are greatly influenced by the grape composition characteristics at harvest. Although Lamb (2004) established good relationships with NDVI and maturity indicators, e.g. Brix and other composition variables (grape phenolics), in this study NDVI displayed correlations of variable consistency with pH, Brix and TA, in agreement with other studies (Acevedo et al. 2008a; Bramley 2005; Hall et al. 2011; Santesteban et al. 2013; Taskos et al. 2014).

Since any changes in vine canopy and environment can influence berry composition characteristics, VIs can only indirectly relate to them. For instance, in high vigour conditions (and thus high NDVI), fruit exposure to sunlight is limited; sunlight is considered essential for flavonoid biosynthesis, for promoting phenolic accumulation (e.g. anthocyanins), and for inducing deep coloration in red cultivars (Jackson 2008; Stamatiadis et al. 2006). Our results confirm the theory that berry composition variables are negatively influenced by vigorous canopies (and thus high in NDVI) probably due to limited sunlight exposure (Drissi et al. 2009; Hall et al. 2011; Koundouras et al. 2009; Lamb et al. 2004; Martinez-Casasnovas et al. 2012; Stamatiadis et al. 2006; Taskos et al. 2013).

Aside from establishing relationships among NDVI and other variables, it was essential to answer important questions, such as whether spatial variability patterns remain stable over time, or whether the spatial variability in yield components is depicted in fruit composition quality attributes. Despite the small vineyard sites (≈ 1 ha), spatial variability was demonstrated among vine water status, NDVI, and berry composition variables. Patterns unveiled by the maps confirmed to a great extent the relationships established from the statistical methods, and particularly the multilinear regression models. Among all variables examined, soil moisture exhibited the highest degree of temporal consistency across the years, followed by the NDVI and the berry composition variables.

By definition high-spatial resolution imagery comprises of reflectance pixels exclusively from the grapevines and not the inter-row space (Hall et al. 2002, 2008). The raw GreenSeeker™ dataset included more than 3000 points, and even after the elimination of the edge pixels (the so called "boundary effects" due to turning manoeuvres), the resulted NDVI maps were of much higher-spatial resolution than maps produced for the rest of the variables explored here. Yet, the experimental plan included ≈ 85 sample vines per vineyard block in order to increase the accuracy of statistics and maps, a number much larger than other studies have used (Bramley 2005; Koundouras et al. 2006; Scarlett et al. 2014; van Leeuwen et al. 2004). Taking into consideration that manual measurements are labour- and cost intensive, the experimental sample size was determined to be suitable for the intentions of this project.

For the results presented in this work, PCA was an appropriate statistical technique to explore the interactions among NDVI and other variables, especially when coupled with the linear regression models. In spite of the fact that not all variability in the dataset was accounted for (≈40%), the relationships revealed were consistent across the methods examined and vintages, and in accordance with current literature. Coupled with PCA, *k*-means clustering analysis for the NDVI further highlighted natural grouping structures associated with important yield and berry composition variables (i.e. phenolics and terpenes). The purpose of *k*-means clustering analysis is to classify similar data together in discrete groupings of high intra-cluster, and low inter-cluster similarity. Markedly, in the case of Coyote's Run Pinot noir (East-West) 2015 high NDVI values prevailed over the lower clusters (65 out of 84 observations) (Figure 3.18b), which can also be depicted in the spread index and CV%, (as the variation increases, the more the individual points affect the clusters) (Table A6), thus providing the PCA observation biplot with no additional information. Moran's *I* results further supported the premise that NDVI follows clustering patterns (Table A22-A27). Therefore, had this study been combined with a sensory evaluation of wines produced from the *k*-means derived NDVI zones, differences in quality attributes expressed by wine profiles might have been more profound.

The Precision Viticulture (PV) approach fundamentally intends to delineate management zones, often by using clustering techniques such as *k*-means clustering, addressed only statistically in this work, as its potential basis for that (Bramley 2005; Tagarakis et al. 2013). For instance, a fuzzy c-means algorithm, a successor of *k*-means, is applied on satellite-acquired imagery, and combined with field data automatically creates zones (Tagarakis et al. 2013). More importantly, the relationships among NDVI and the variables of interest have to be systematized across a variety of grapevine cultivars, soil types (particularly in the case of water zones) and broader topographical regions before the wider applicability of the proximal sensing technology is accepted (Acevedo-Opazo et al. 2008a; Bramley 2010; Stamatiadis et al. 2009). Calibration of VIs will allow for easier comparison across sites and interpretation of the values. Essentially, vineyards divided into sub-blocks of characteristic performance will grant growers the opportunities for not only a more effective vineyard management, but also for improved winemaking.

3.6 CONCLUSIONS

The primary objective of this work was to test the proximal sensing monitoring system GreenSeeker™ against variables of agricultural relevance. Results obtained through the GreenSeeker™ are considered sufficient in terms of repeatability and correlations, as the nature of the relationships was consistent across the statistical methods employed. Grapevine canopies can encounter many environmental biophysical constraints, such as low soil water availability, and therefore reflect less light (low NDVI). Our results confirmed that yield components and vine vigour (indicated by pruning weights) were important factors in NDVI variability, while berry composition variables (i.e. anthocyanins, colour, phenols, monoterpenes) showed strong consistent inverse relationships with NDVI. Therefore, the GreenSeeker™ usefulness was exhibited not only through the consistency of the relationships established, although the strength of these correlations was limited in most cases, but also through the simplicity of the procedure, in comparison with remote sensing or passive proximal sensors. Spaceborne or airborne acquired remote sensing imagery requires manual delineation of the rows, elimination of non-vine pixels (e.g. cover crop) and is restricted to weather conditions (cloud cover). Maps produced for all variables examined here demonstrated strongly the spatial variability in the vineyard scale, which is indicative that zonal management could be potentially feasible.

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3.8 TABLES

3.8.1 LINEAR REGRESSION MODEL RESULTS

Table 3.1 Linear regression test results for all blocks in 2014 and 2015.
Confidence interval : 95%. Root mean square error of the regression line (RMSE) is expressed as NDVI unit. Significant levels are reported as follows: * = *p*<0.05, ** = *p*<0.01 and *** = *p*<0.001.

VINEYARD SITE	*VARIETY*	*YEAR*	*Mean NDVI =*	*Adjusted R^2*	*RMSE*	*Significant Variables*
LAMBERT	CABERNET FRANC	**2014**	0.74+6.24E-03*Brix-4.15E-02*pH+7.11E-03*TA-1.20E-05*Phenols-3.56E-02*Leaf ψ	0.320	0.010	Brix ***, TA*, Phenols***, Leaf ψ*
		2015	0.68+1.21E-03*Brix+2.09E-02*pH-7.94E-04*Colour+2.09E-02*Leaf ψ	0.132	0.010	Colour*
	RIESLING	**2014**	0.70-1.49E-04*Cluster#+2.73E-03*TA+0.019*PVT-0.027*Leaf ψ	0.378	0.009	Cluster number**, TA*, PVT***
		2015	0.79+4.01E-04*Brix-9.91E-03*FVT +1.89E-03*PVT +4.79E-03*Vine size-1.14E-03*Soil moisture	0.178	0.005	Soil Moisture **
CAVE SPRING	CABERNET FRANC	**2014**	0.89-1.22E-03*Cluster#+6.01E-03*Yield-3.58E-04*Berry weight-6.97E-05*Anthocyanins+2.71E-02*Vine size	0.379	0.014	Cluster number*, Berry weight**, Anthocyanins ***, Vine size **
		2015	0.79-5.74E-04*Cluster #+2.80E-03*Yield+1.0E-02*Vine Size-5.25E-04*Soil Moisture-2.34E-02*Leaf ψ	0.226	0.007	Cluster number**, Yield*, Vine size**
	RIESLING	**2014**	0.82-1.20E-03*Cluster #+5.51E-03*Yield-4.57E-02*FVT -8.49E-03*PVT	0.225	0.011	Cluster number***, Yield***, FVT*
		2015	0.76+3.62E-03*TA-3.42E-02*FVT +1.53E-02*Vine Size	0.135	0.013	TA**, FVT*
COYOTE'S RUN	PINOT NOIR (E-W)	**2014**	1.01-1.38E-03*Cluster#+7.84E-03*Yield+4.53E-03*Brix -6.89E-02*pH+2.75E-03*LT_{50}	0.170	0.016	Cluster number*, Brix**, pH**
		2015	0.78+7.41E-03*Yield+6.85E-03*TA+1.75E-05*Phenols -1.18E-03*Soil Moisture+8.82E-02*Leaf ψ	0.101	0.024	TA *, Phenols *, Leaf ψ * *
	PINOT NOIR (N-S)	**2014**	0.63+5.79E-03*Yield-4.23E-03*Brix+8.21E-02*pH+1.05E-04*Anthocyanins+3.38E-03*Mean LT_{50}	0.227	0.015	Yield**, Brix*, pH***, Anthocyanins**, Mean LT_{50}*
		2015	0.78+1.50E-04*Cluster number+6.52E-03*Vine Size+8.06E-04*Soil Moisture+2.24E-02*Leaf ψ	0.137	0.008	Soil Moisture *

3.8.2 PEARSON'S CORRELATIONS

Table 3.2 Pearson's correlation coefficients for NDVI for all fields in 2014 and 2015. Only variables with significant relationships were included, and empty cells represent no relationship. Significance levels are indicated as follows: p<0.05 bold, p<0.01 bold and underlined, and p<0.001 bold and double underlined.

NDVI																					
VINEYARD SITE	*VARIETY & YEAR*	Cluster number	Yield (kg/vine)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
Lambert	*Cabernet franc 2014*			0.270		0.262			-0.313									-0.265			
	Cabernet franc 2015				0.298			-0.263									-0.421		0.320		
Cave Spring	*Cabernet franc 2014*			-0.292	-0.228		-0.465	-0.351	-0.403	0.425						0.230					0.395
	Cabernet franc 2015									0.351						0.231			-0.240	-0.249	0.269
Coyote's Run	*Pinot noir EW 2014*				-0.314		-0.248								0.217		-0.223				
	Pinot noir EW 2015																0.377	0.280		0.261	
	Pinot noir NS 2014	0.241	0.247								0.452	-0.333	0.208								
	Pinot noir NS 2015	0.263								0.210			0.322	0.221		0.271					

NDVI																		
VINEYARD SITE	*VARIETY & YEAR*	Cluster number	Yield (kg/vine)	Soluble Solids (°Brix)	pH	Free Volatile Terpenes (mg/L)	Potentially Volatile Terpenes (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
Lambert	*Riesling 2014*	-0.260	-0.300	0.267	0.230	0.357	0.545								-0.369		-0.276	
	Riesling 2015					-0.277			-0.850		-0.308	-0.405	-0.253	-0.385		-0.250		
Cave Spring	*Riesling 2014*					-0.274				0.252								0.416
	Riesling 2015					-0.282		0.234										

3.9 FIGURES

3.9.1 NDVI REGRESSION SCATTERPLOTS

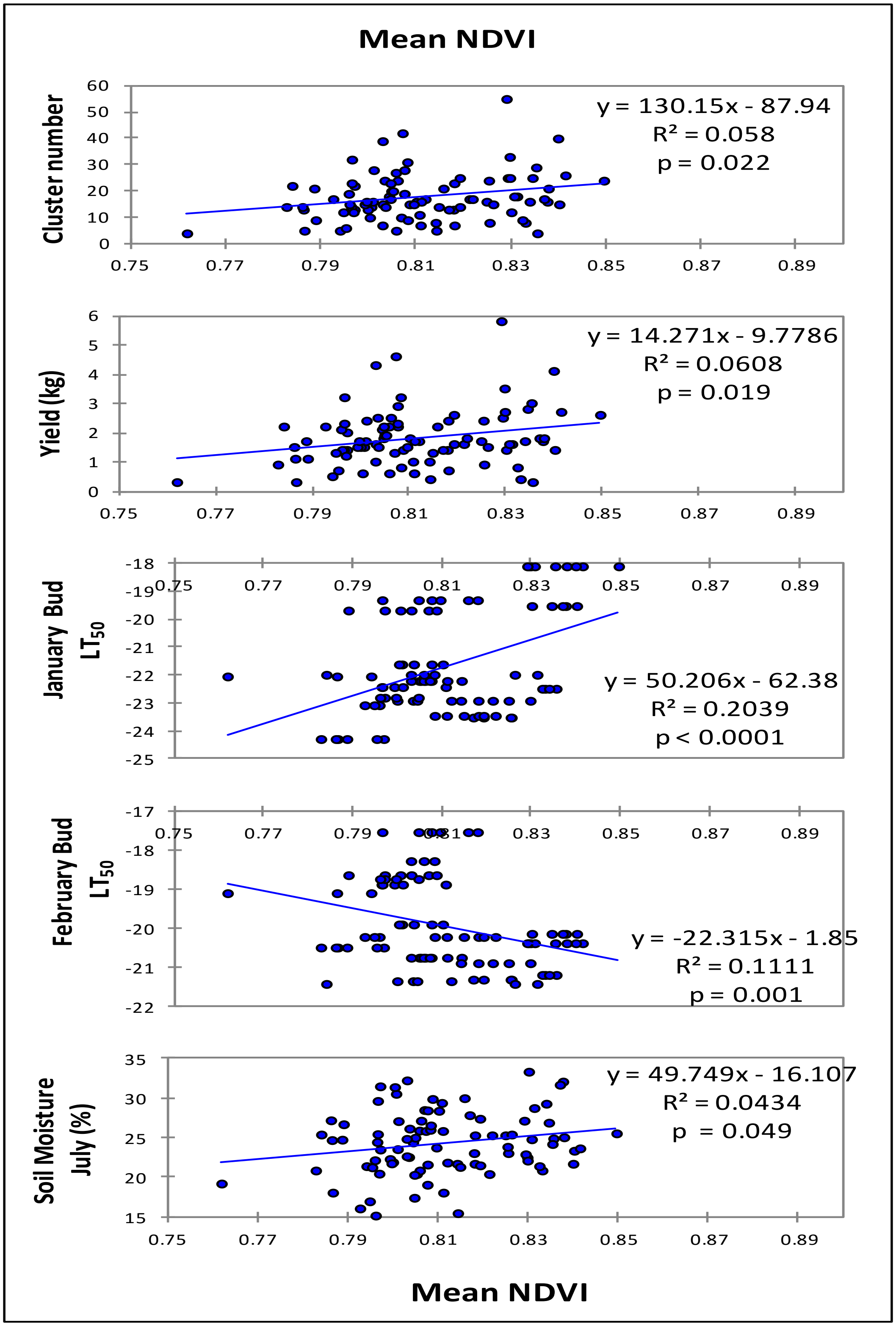

Figure 3.1 Coyote's Run Pinot noir North-South 2014: Cluster number, yield (kg), January LT_{50}, February LT_{50}, and soil moisture July (%) vs. mean NDVI scatterplot.

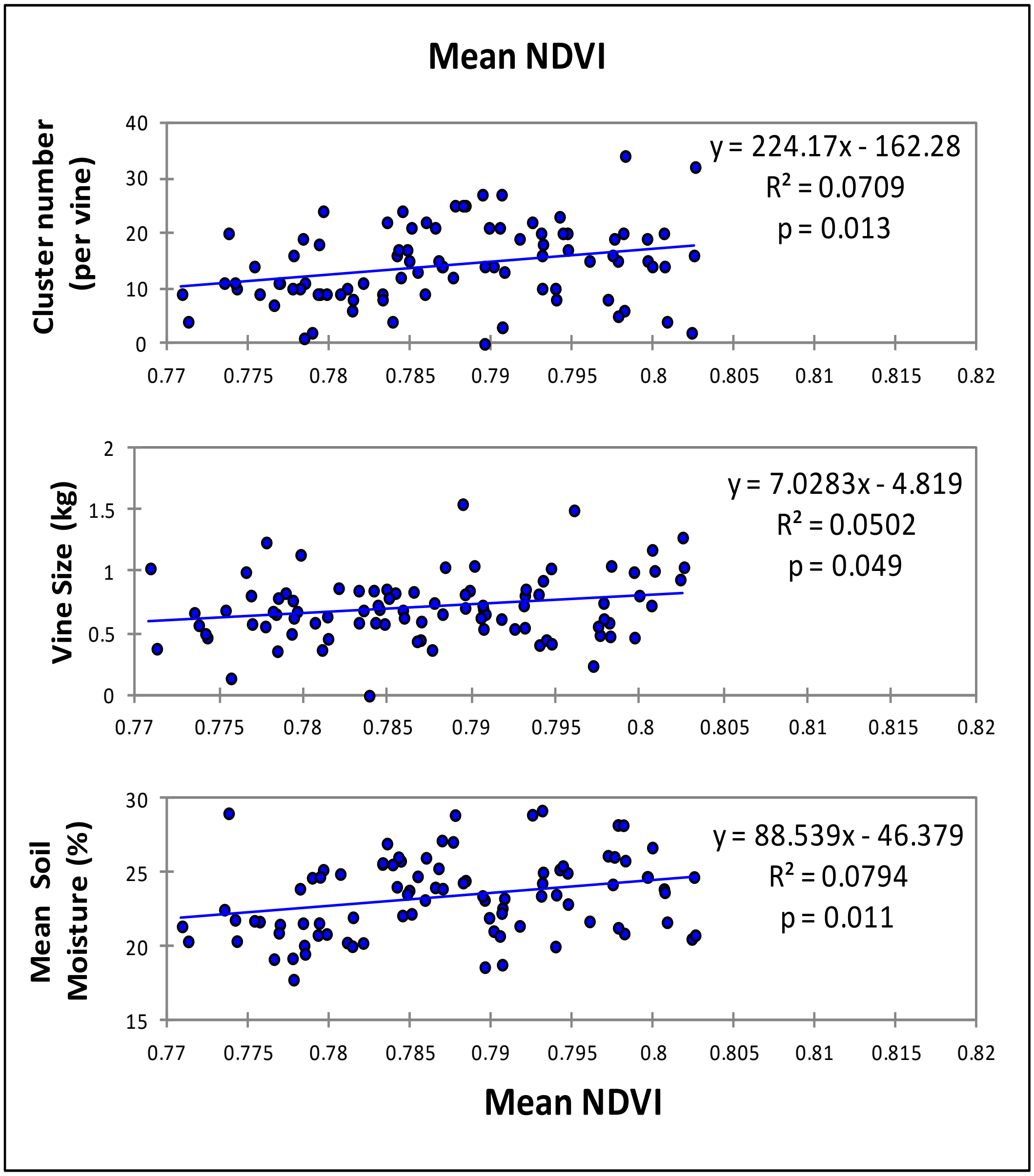

Figure 3.2 Coyote's Run Pinot noir North-South 2015: Cluster number, vine size (kg), and mean soil moisture vs. mean NDVI scatterplot.

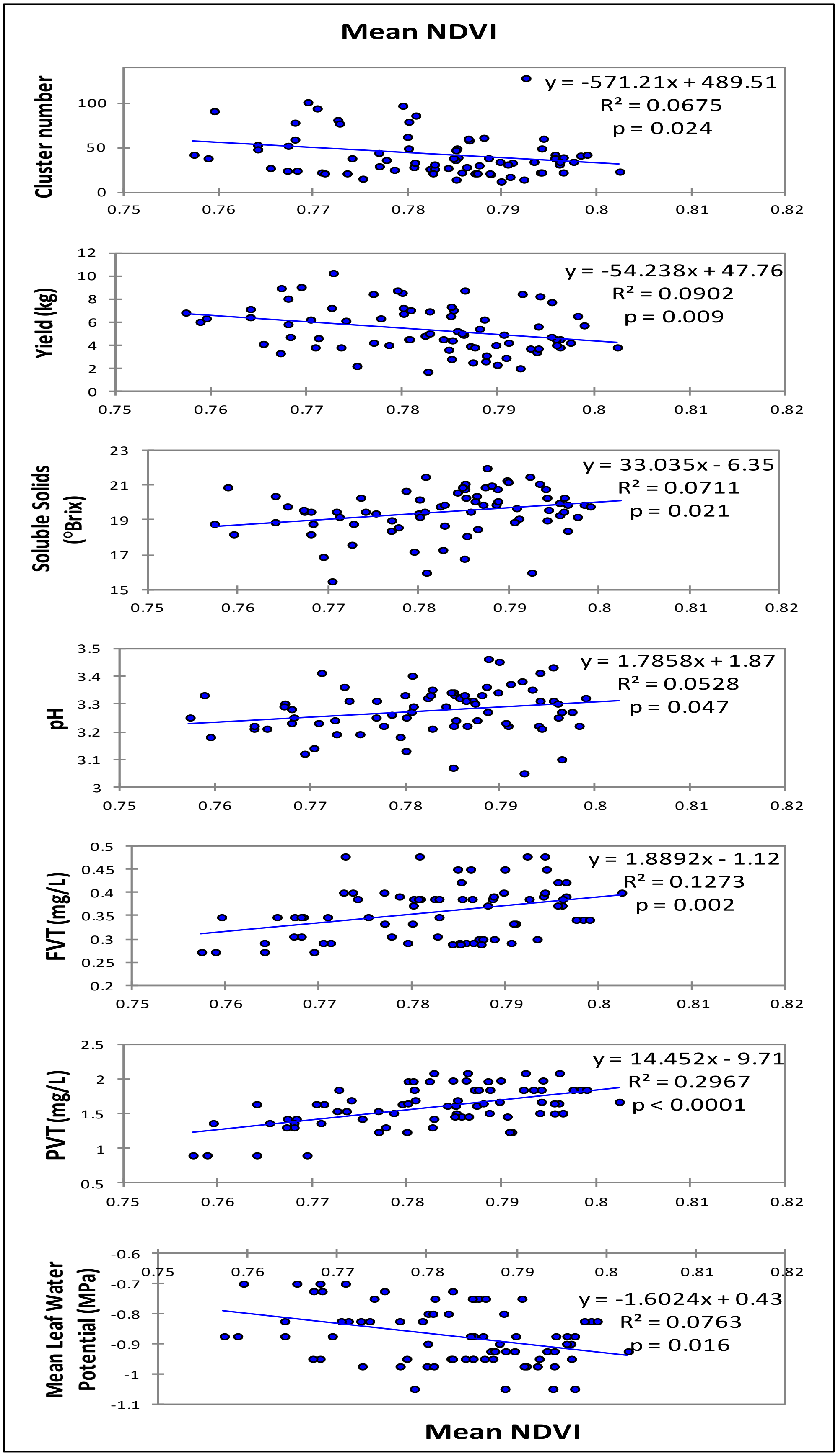

Figure 3.3 Lambert Riesling 2014: Cluster number, yield (kg), Soluble solids (°Brix), pH, free-volatile, and potentially-volatile terpenes (mg/L), and mean leaf water potential (MPa) vs. mean NDVI scatterplot.

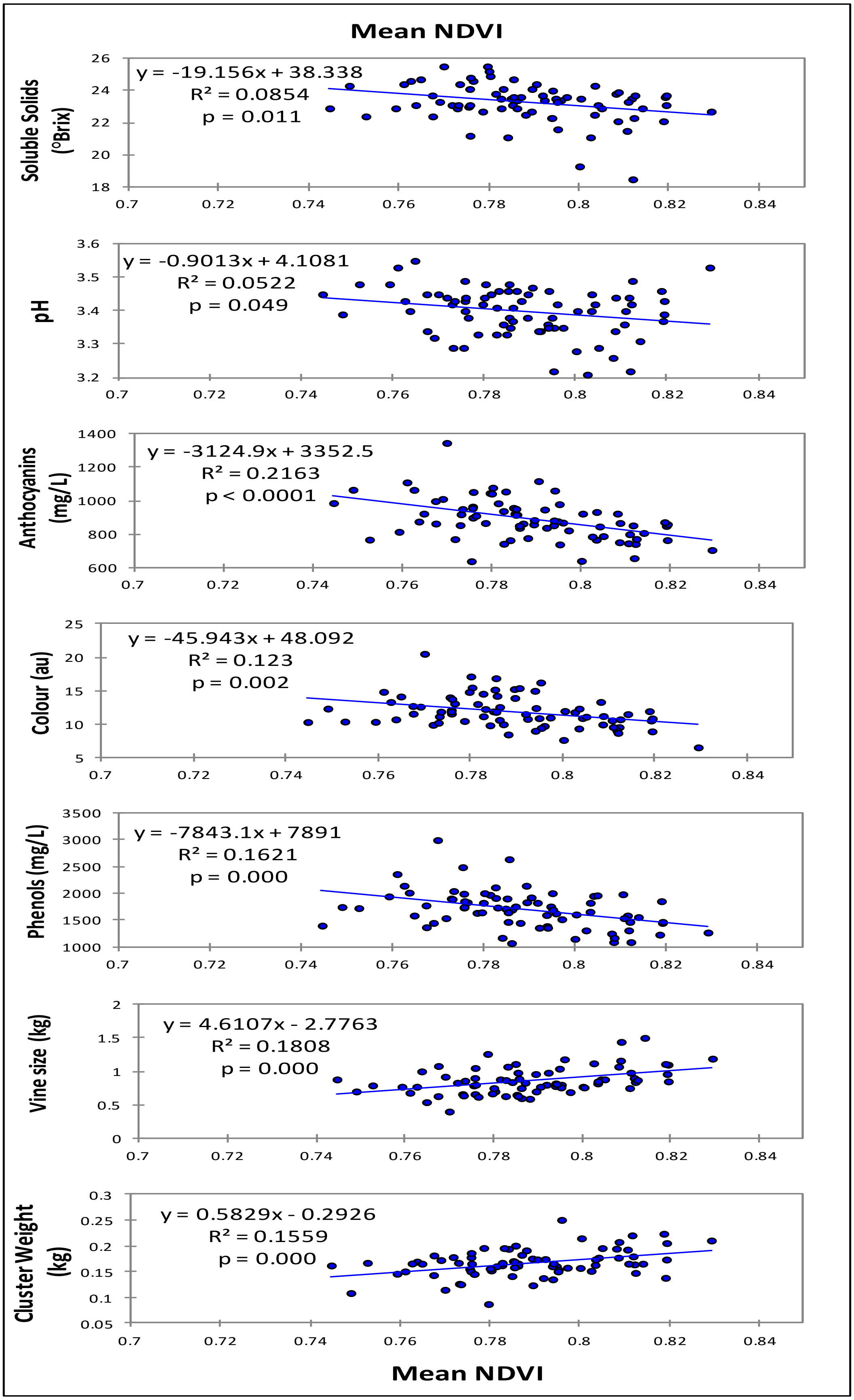

Figure 3.4 Cave Spring Cabernet franc 2014: Soluble solids (°Brix), pH, anthocyanins (mg/L), Colour (au), phenols (mg/L), vine size (kg), and cluster weight (kg) vs. mean NDVI scatterplot.

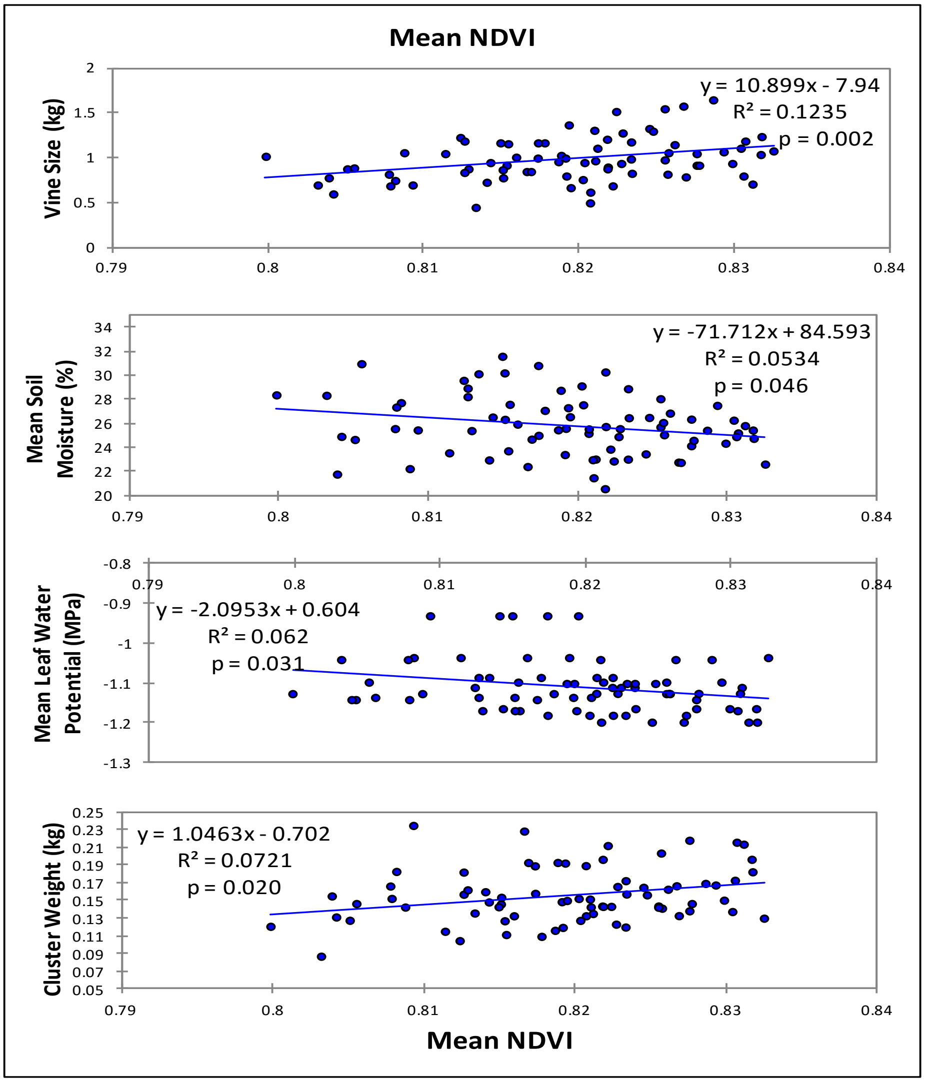

Figure 3.5 Cave Spring Cabernet franc 2015: Vine size (kg), mean soil moisture (%), mean leaf water potential (MPa), and cluster weight (kg) vs. mean NDVI scatterplot.

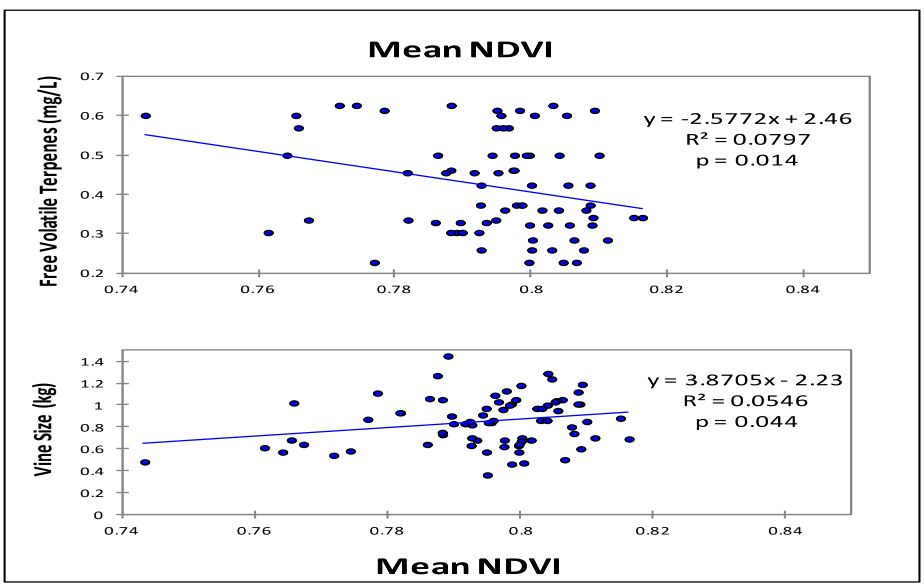

Figure 3.6 Cave Spring Riesling 2015: Free volatile terpenes (mg/L), and vine size (kg) vs. mean NDVI scatterplot.

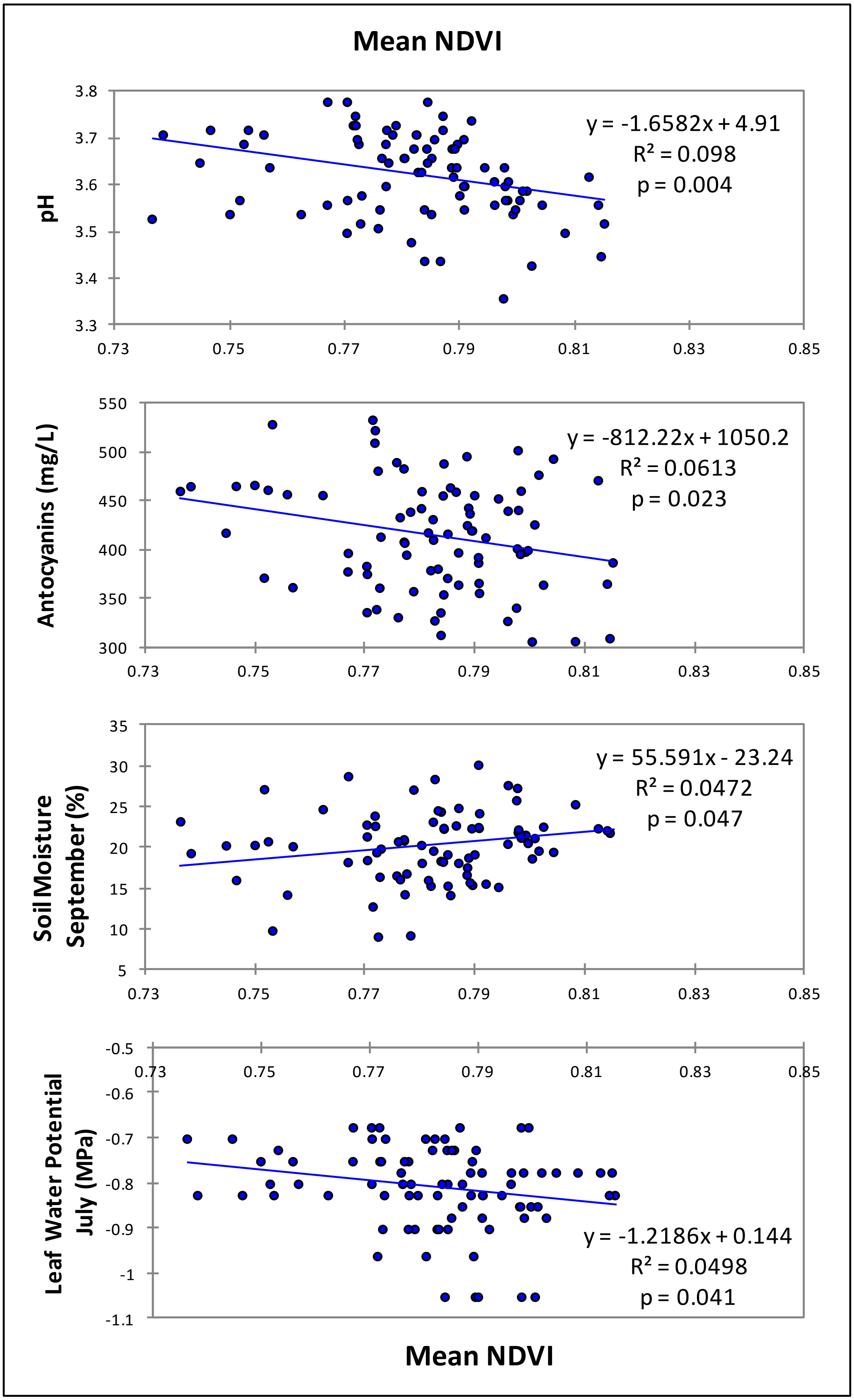

Figure 3.7 Coyote's Run Pinot noir East-West 2014: pH, anthocyanins (mg/L), soil moisture September (%), and leaf water potential July vs. mean NDVI scatterplot.

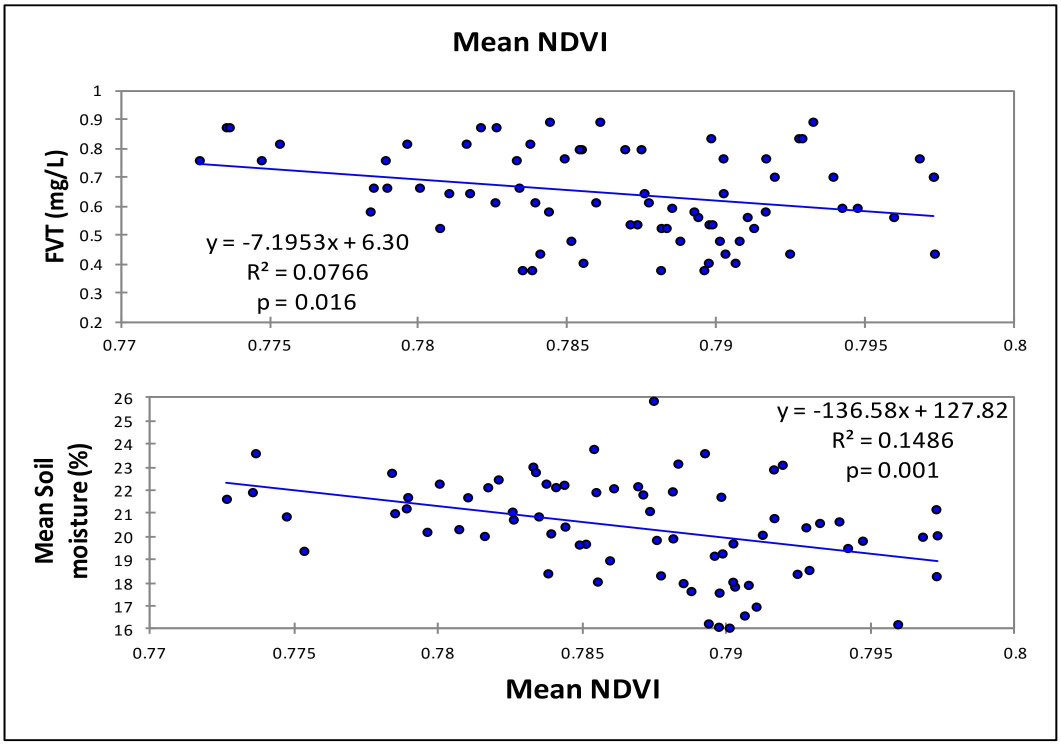

Figure 3.8 Lambert Riesling 2015: Free volatile terpenes (mg/L), and mean soil moisture (%) vs. mean NDVI scatterplot.

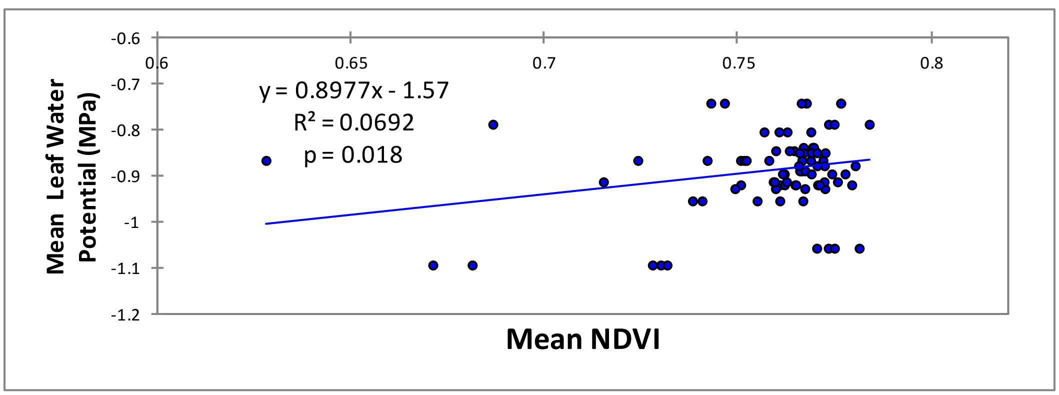

Figure 3.9 Coyote's Run Pinot noir East-West 2015: Mean leaf water potential vs. mean NDVI scatterplot.

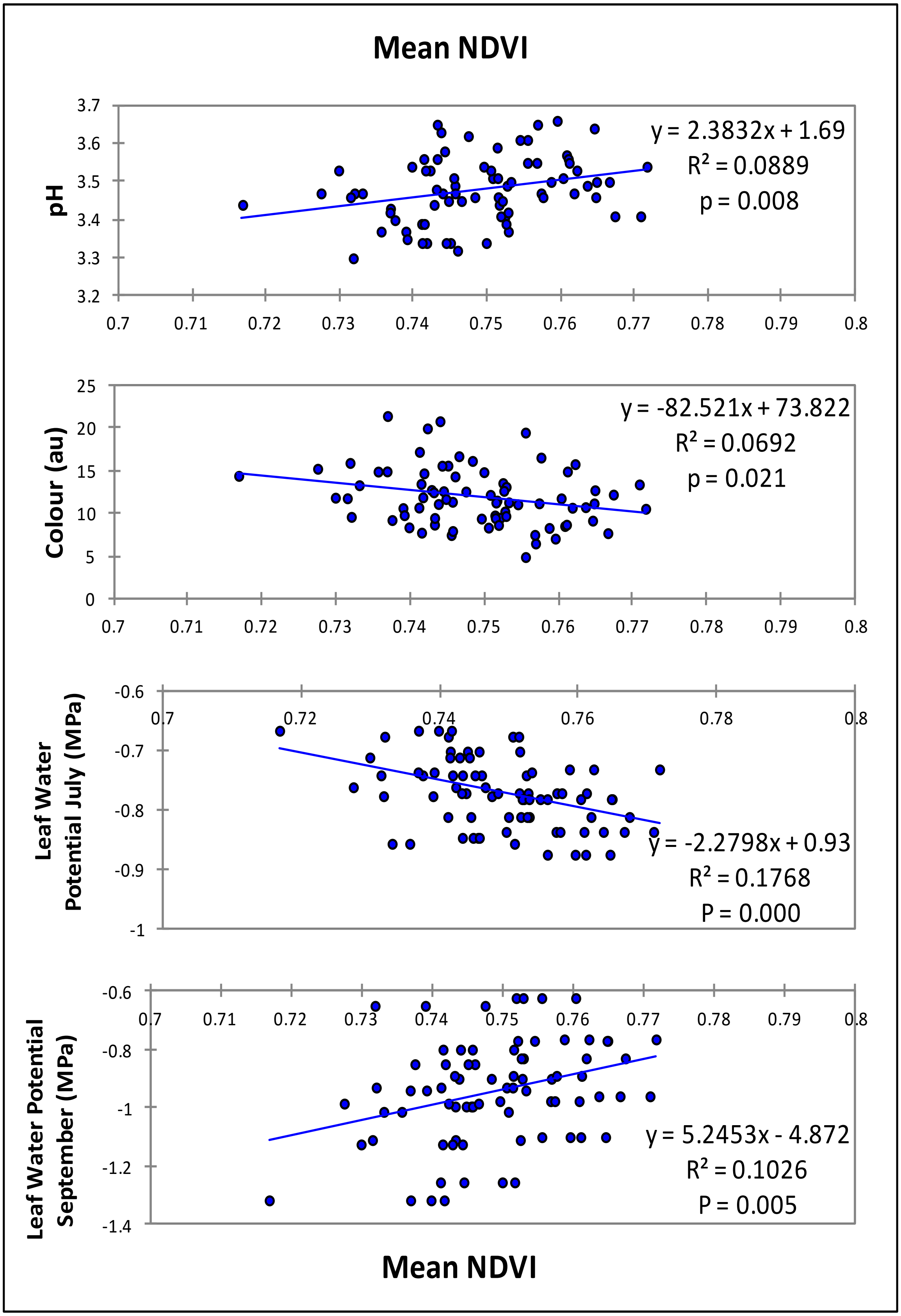

Figure 3.10 Lambert Cabernet franc 2015: pH, colour (au), leaf water potential July, and leaf water potential September (MPa) vs. mean NDVI scatterplot.

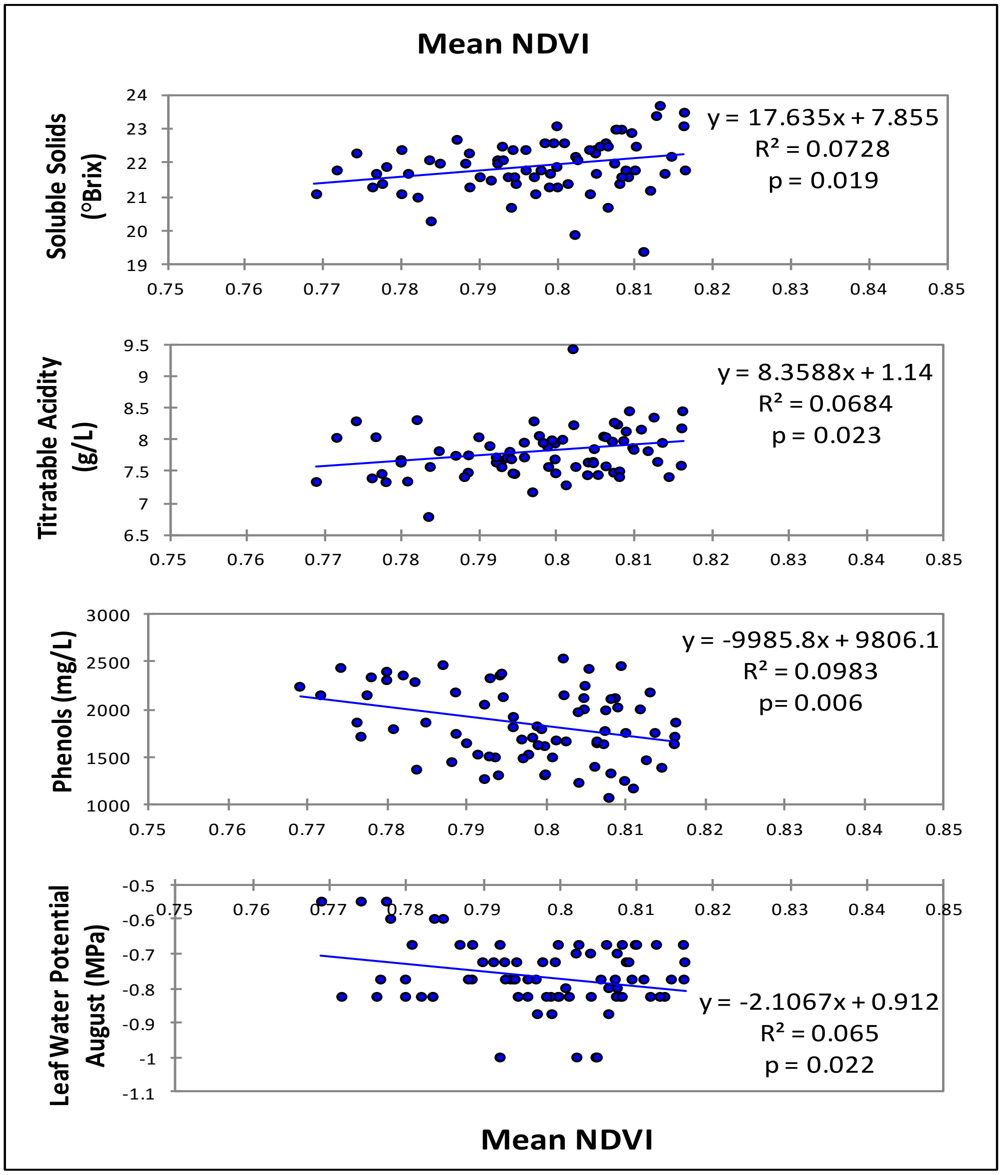

Figure 3.11 Lambert Cabernet franc 2014: Soluble solids (°Brix), titratable acidity (g/L), phenols (mg/L) and leaf water potential August (MPa) vs. mean NDVI scatterplot.

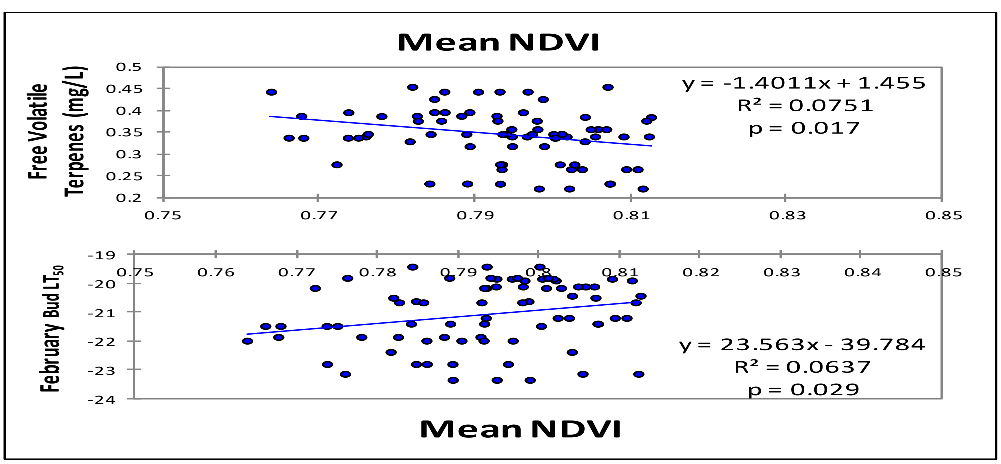

Figure 3.12 Cave Spring Riesling 2014: Free volatile terpenes (mg/L), and February LT_{50} vs. mean NDVI scatterplot.

3.9.2 PRINCIPAL COMPONENT ANALYSIS (NDVI)

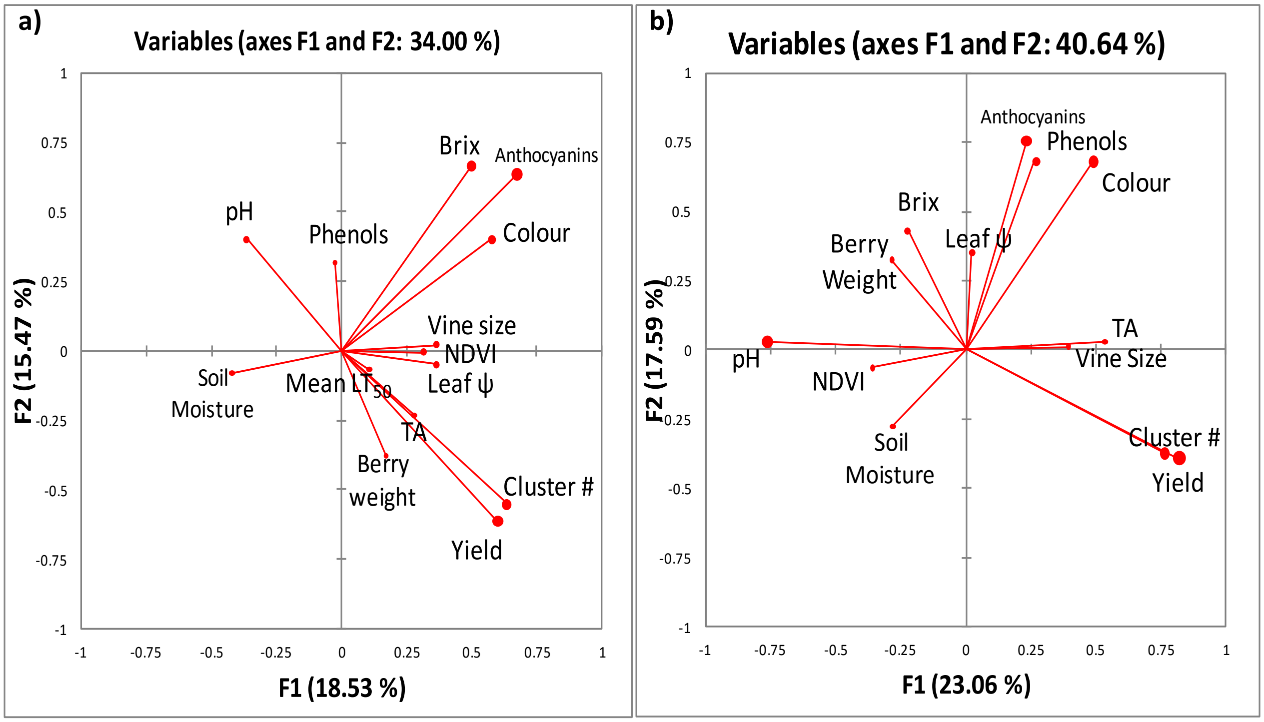

Figure 3.13 Principal component analysis for Lambert Cabernet franc: a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics, and NDVI. Abbreviations: TA=Titratable acidity.

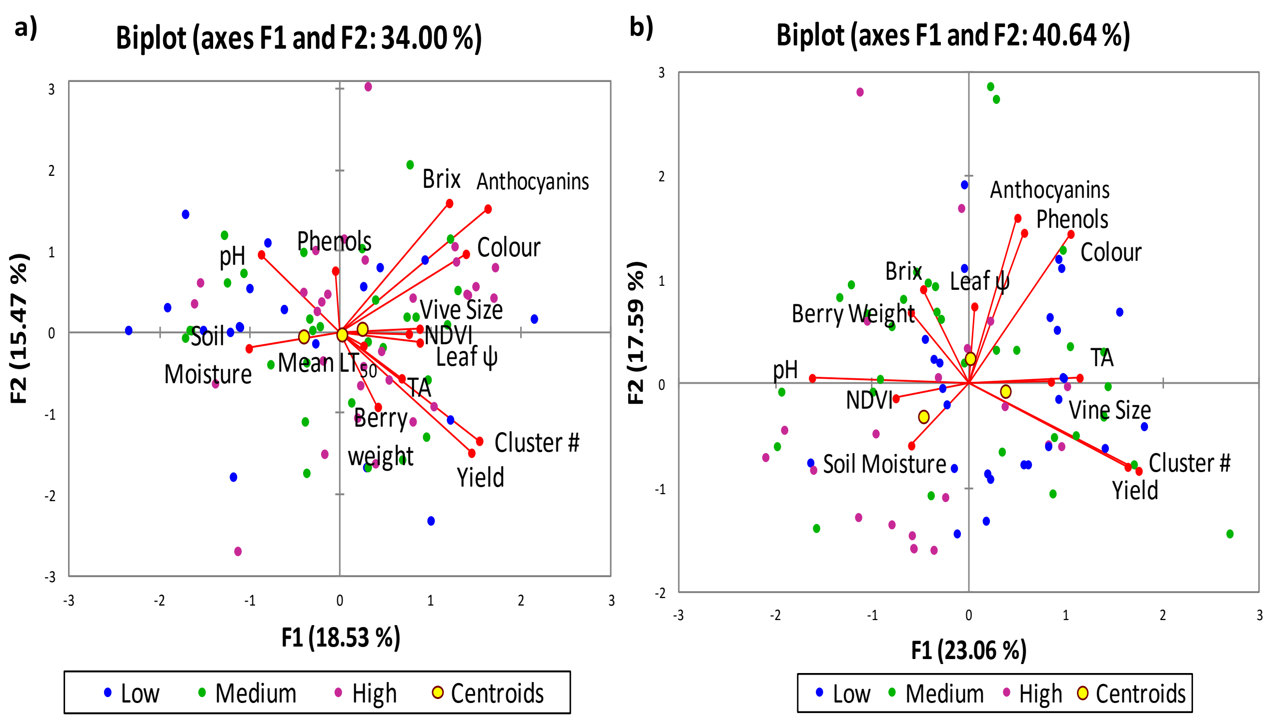

Figure 3.14 Principal component analysis correlation biplot of observations for Lambert Cabernet franc: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high NDVI levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

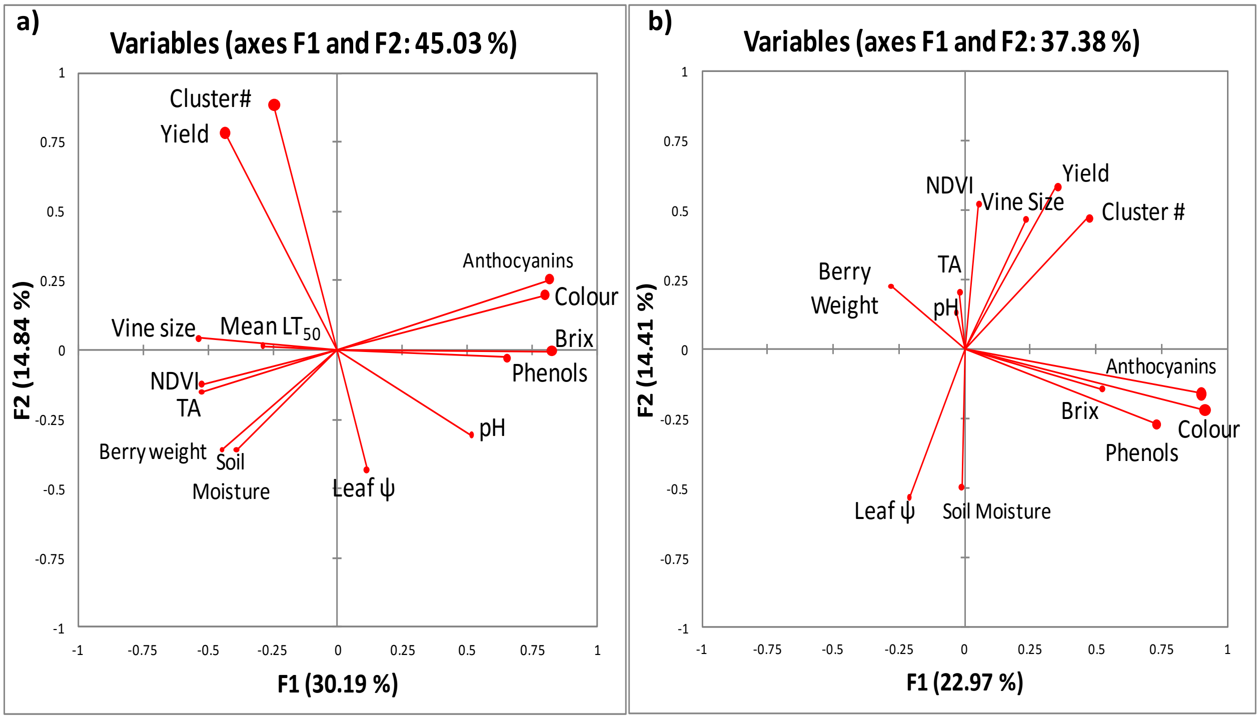

Figure 3.15 Principal component analysis for Cave Spring Cabernet franc: a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and NDVI. Abbreviations: TA=Titratable acidity.

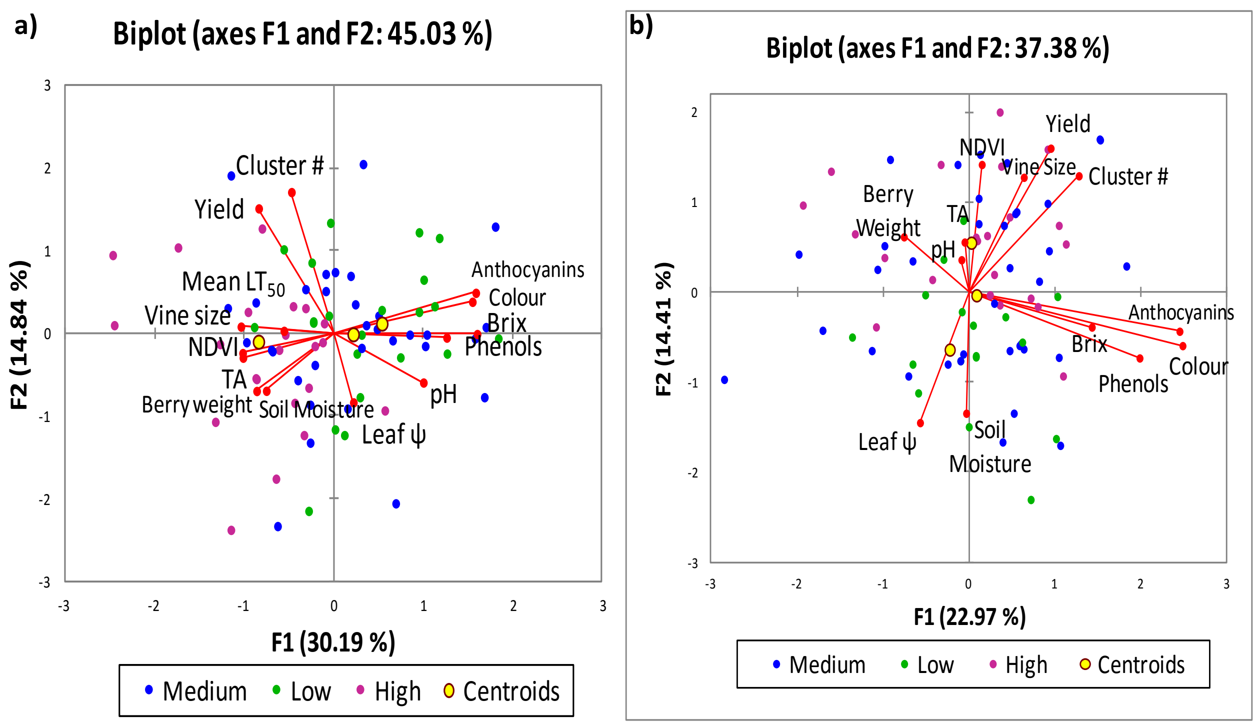

Figure 3.16 Principal component analysis correlation biplot of observations for Cave Spring Cabernet franc: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high NDVI levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

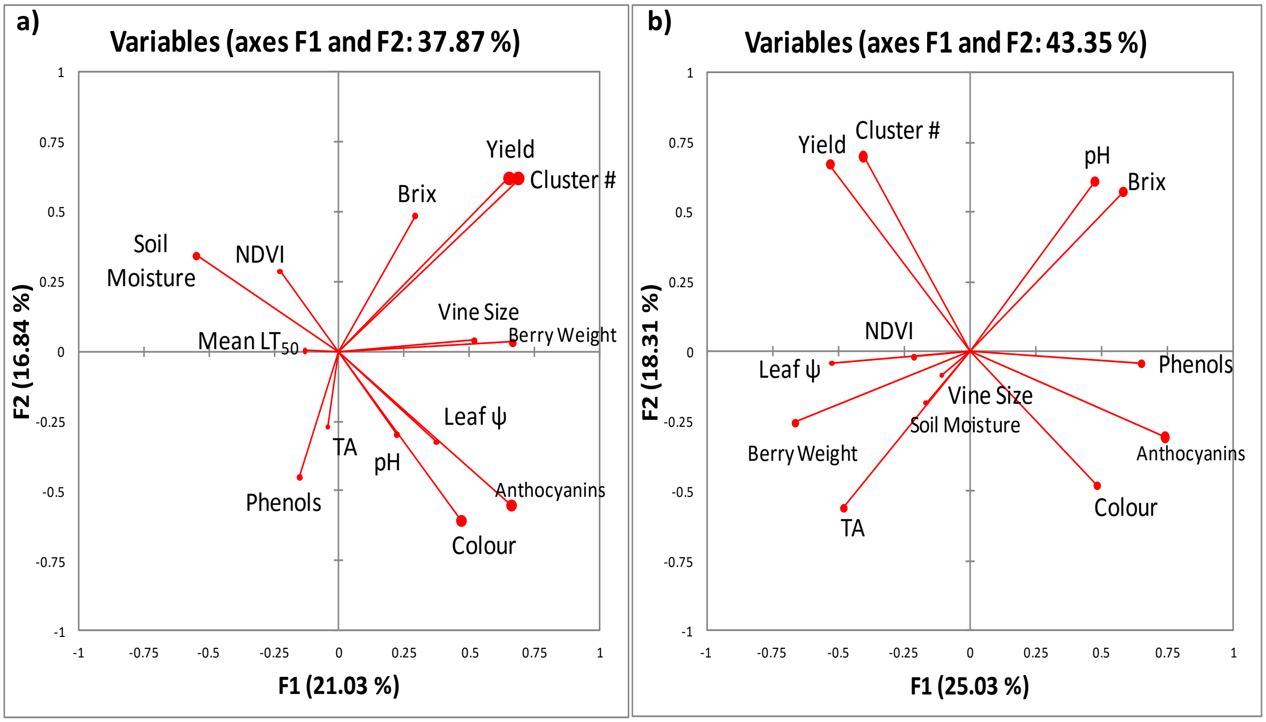

Figure 3.17 Principal component analysis for Coyote's Run Pinot noir (East-West): a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and NDVI. Abbreviations: TA=Titratable acidity.

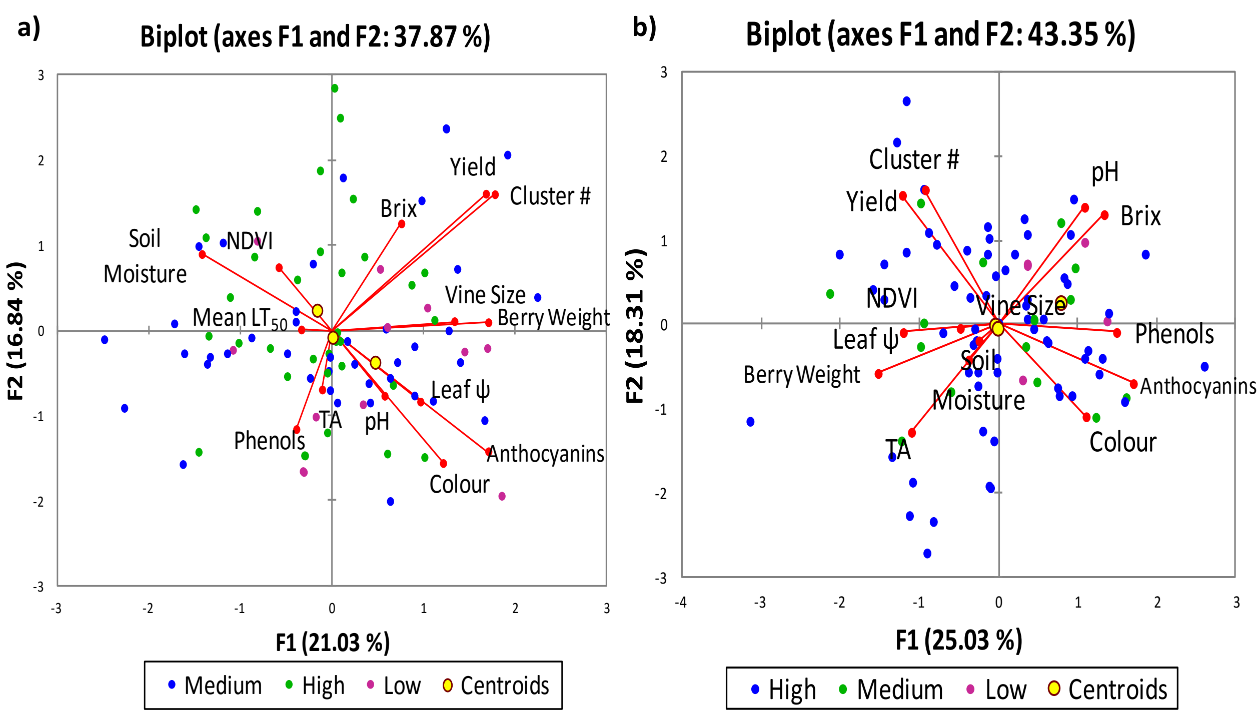

Figure 3.18 Principal component analysis correlation biplot of observations Coyote's Run Pinot noir (East-West): a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high NDVI levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

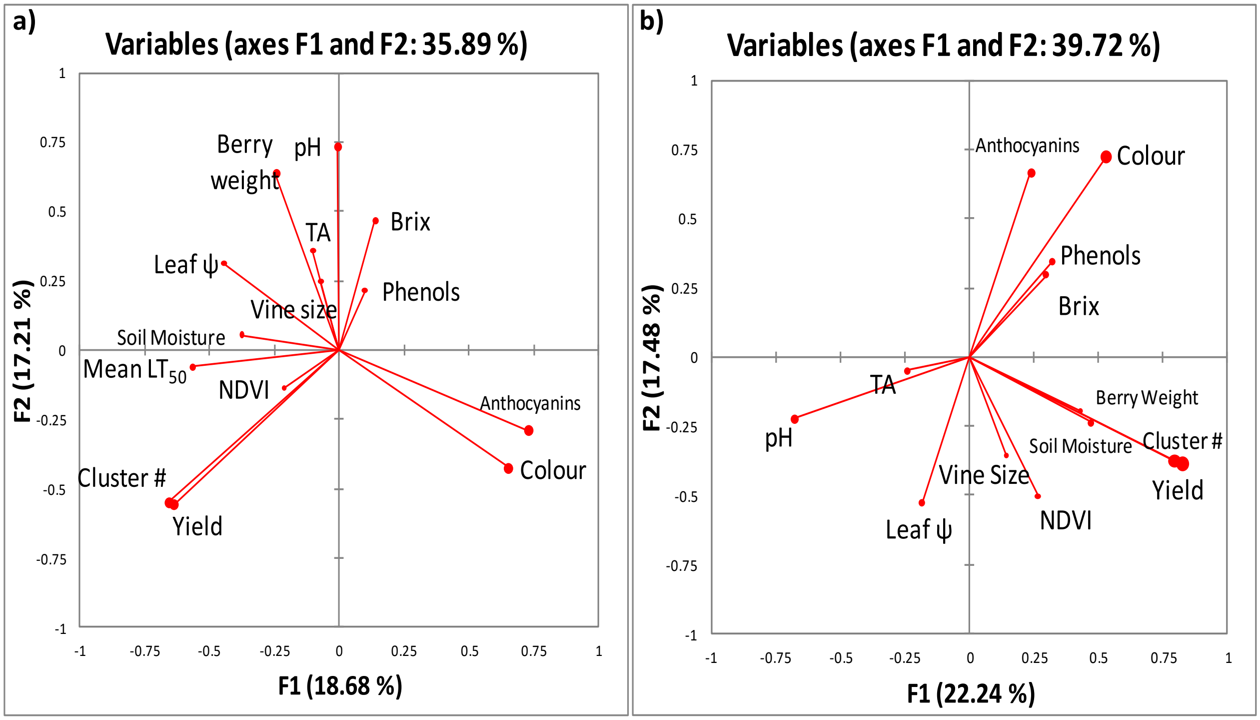

Figure 3.19 Principal component analysis for Coyote's Run Pinot noir (North-South): a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics, and NDVI. Abbreviations: TA=Titratable acidity.

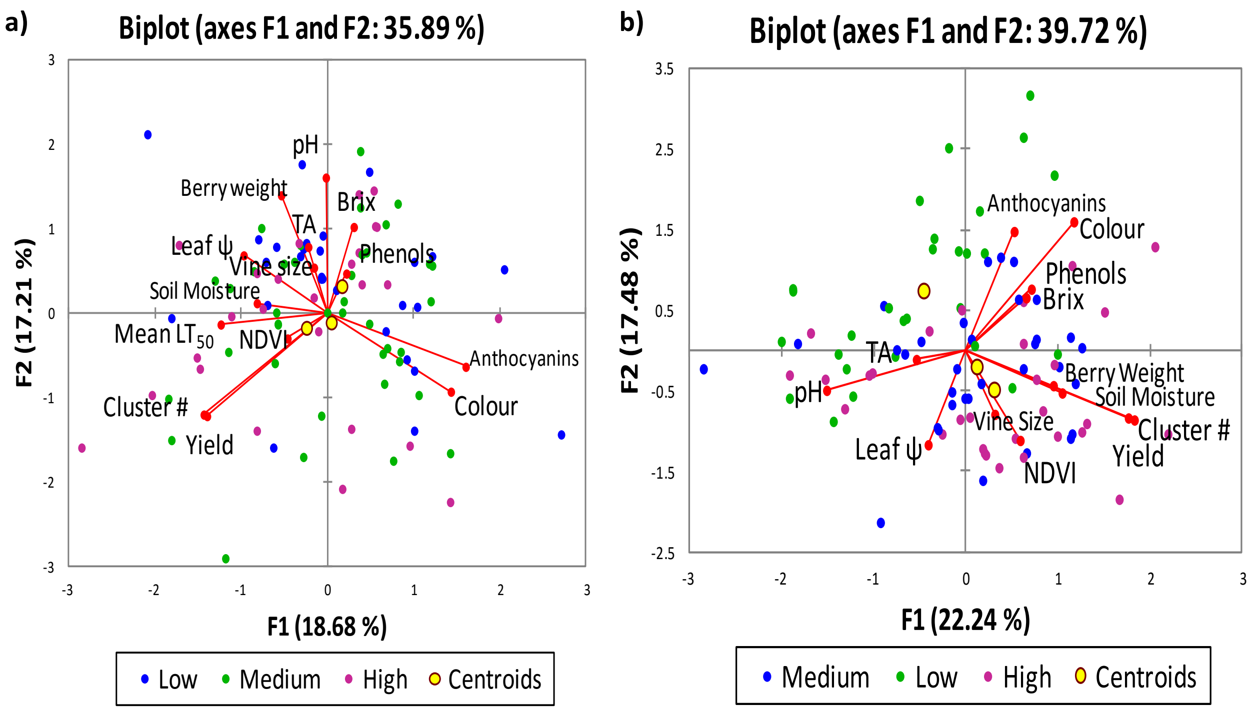

Figure 3.20 Principal component analysis correlation biplot of observations for Coyote's Run Pinot noir (North-South): a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high NDVI levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity.

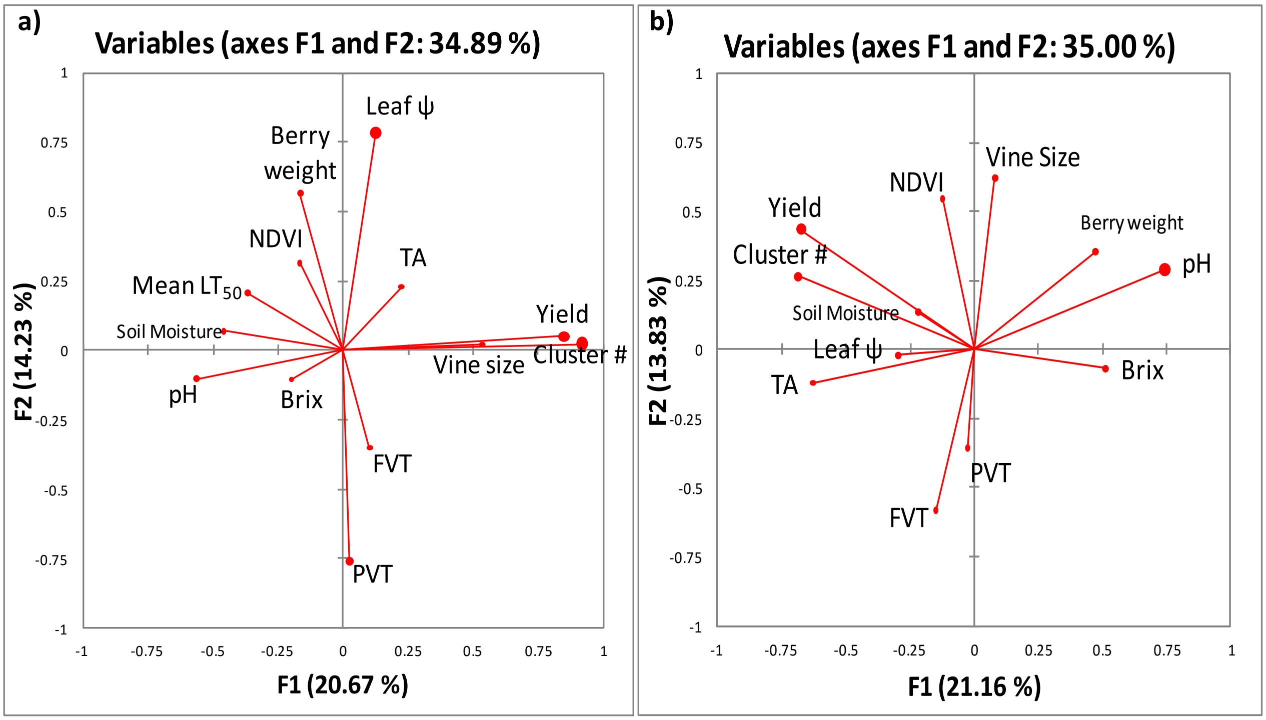

Figure 3.21 Principal component analysis for Cave Spring Riesling: a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and NDVI. Abbreviations: TA=Titratable acidity; FVT=free volatile terpenes; PVT=potentially volatile terpenes.

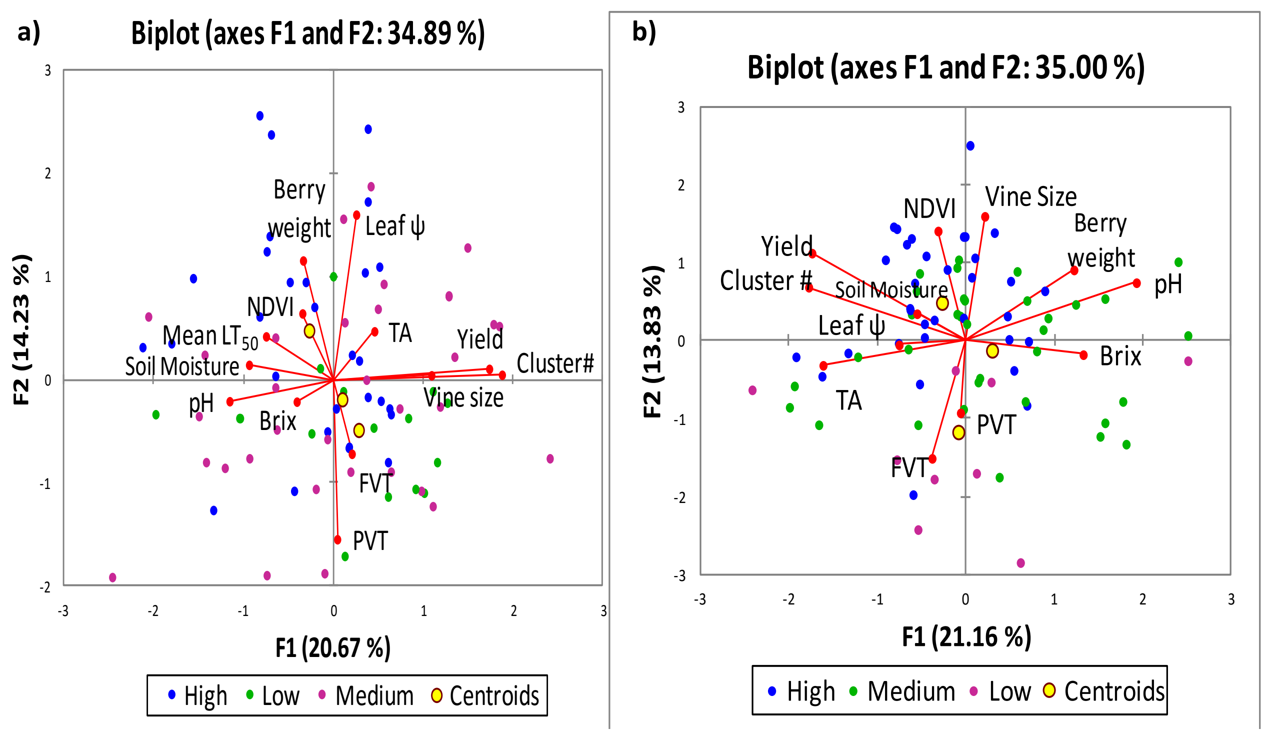

Figure 3.22 Principal component analysis correlation biplot of observations for Cave Spring Riesling: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high NDVI levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity; FVT=free volatile terpenes; PVT=potentially volatile terpenes.

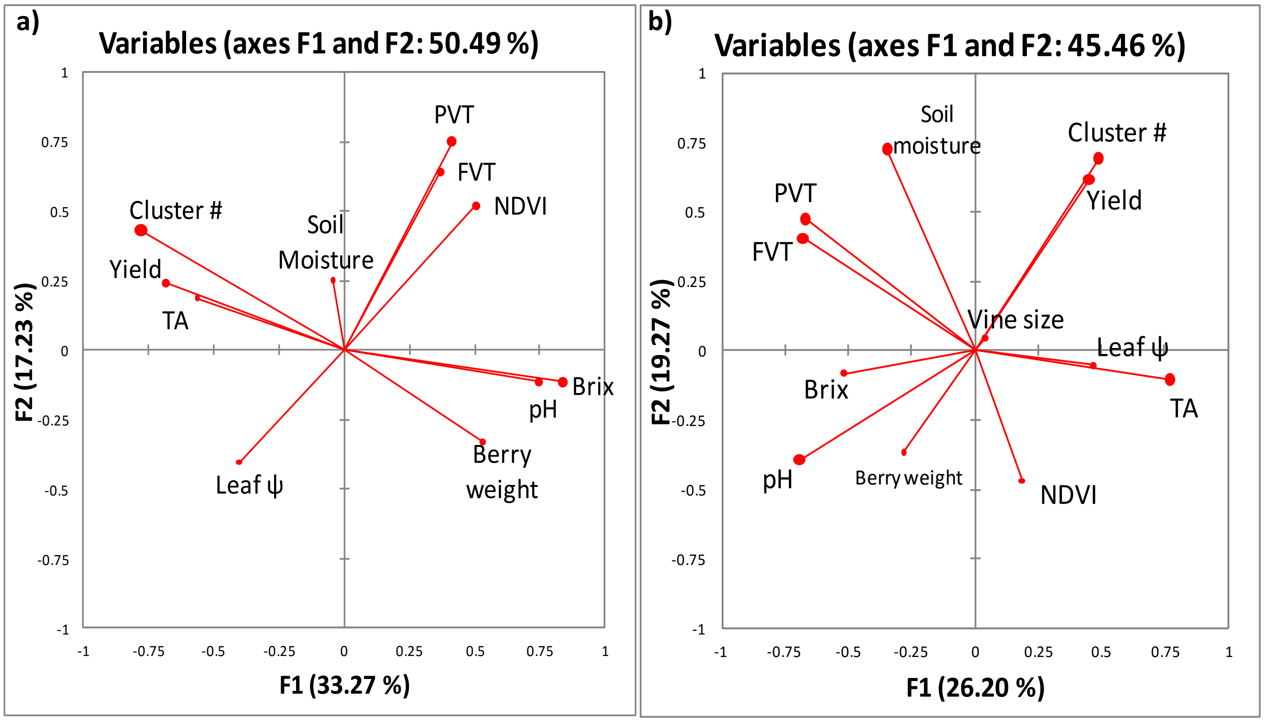

Figure 3.23 Principal component analysis for Lambert Riesling: a) 2014, and b) 2015. Variables include vine water status, berry composition characteristics and NDVI. Abbreviations: TA=Titratable acidity; FVT=free volatile terpenes; PVT=potentially volatile terpenes.

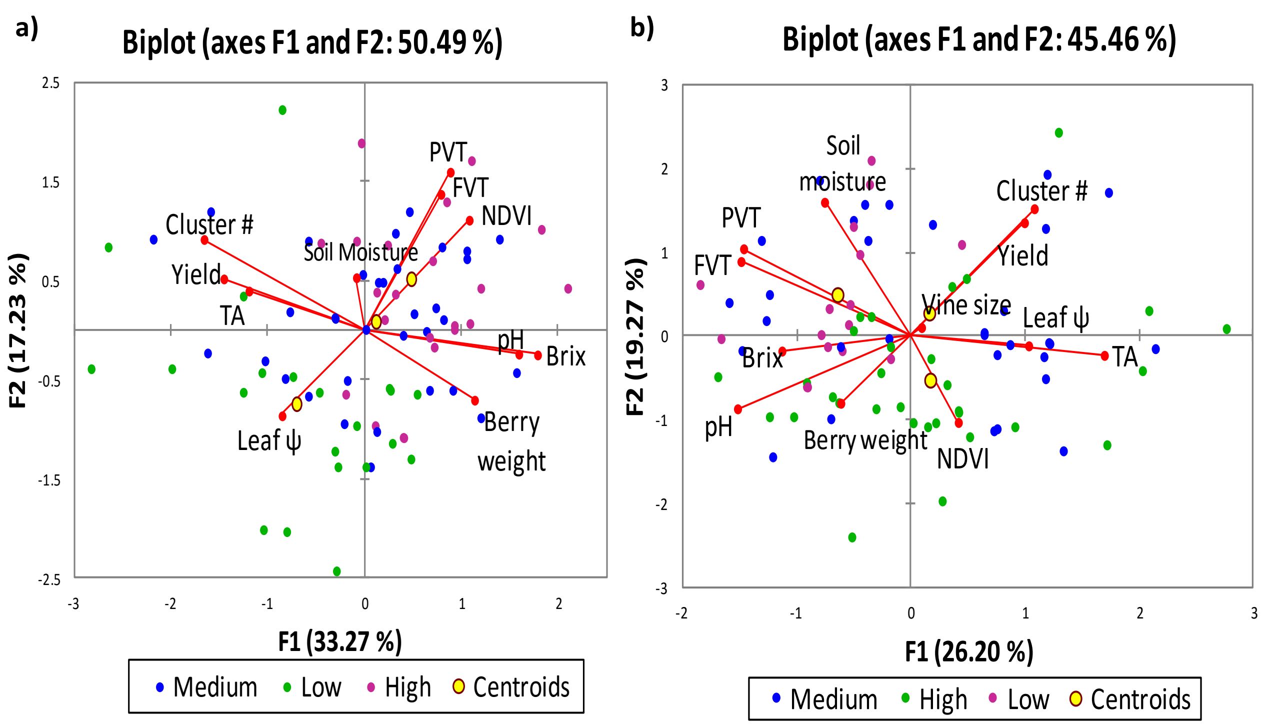

Figure 3.24 Principal component analysis correlation biplot of observations for Lambert Riesling: a) 2014, and b) 2015. The observations are classified with *k*-means clustering to low, medium, and high NDVI levels. Class centroids are displayed in yellow. Abbreviations: TA=Titratable acidity; FVT=free volatile fterpenes; PVT=potentially volatile terpenes.

a) b)

Figure 3.25 GreenSeeker™ proximal sensing technology is mounted on a metal frame on a four-wheel-drive vehicle (a) and collects geo-referenced NDVI data from each sensor (b), Coyote's Run Winery, St. David's Bench, Ontario, Canada. Personal photographs by author, 2014.

CHAPTER 4 : GENERAL DISCUSSION AND CONCLUSIONS

The overall objective of this thesis was to investigate and validate the usefulness of proximal sensing technology, namely the GreenSeeker™, for making inferences about grapevine physiological indicators, such as yield components, vigour, vine water status and fruit composition in Ontario vineyards over two growing seasons (i.e. 2014-2015) by the calculation of the Normalized Difference Vegetation Index (NDVI). The implementation of geospatial technologies in viticulture, including geographical information systems (GIS), remote sensing, and differential global positioning system (dGPS), along with the application of various statistical procedures intended to explore vineyard variability and potentially determine unique sub-blocks in the vineyard study blocks in terms of physiology, productivity, and berry composition. The relationships among variables of viticultural importance, such as yield components and fruit composition were initially measured and validated (first part of the study) and thereafter assessed against the geospatial datasets acquired from the GreenSeeker™ technology (second part of the study).

Initially, it was hypothesized that soil moisture and leaf ψ would establish correlations with yield components, vigour and berry composition variables, whereby increased water availability in the vine would relate to higher yield, vigour and berry weight, but to lower desirable berry composition characteristics. The results were partially in agreement with the hypotheses. Leaf ψ was related to berry size, but not to yield in all cases, while high yield was correlated with vine vigour in some study blocks. The second part of the hypotheses was entirely verified; low soil moisture directly promoted higher concentrations of phenolics in Cabernet franc and Pinot noir blocks in both vintages, while low leaf ψ (high water stress) was associated with high monoterpene concentrations in Riesling, particularly with PVTs.

In the second part of this study, it was hypothesized that variability in vegetative expression, yield components and vine water status would associate with the NDVI measurements, acquired from the GreenSeeker™, and that profound relationships with grape quality indicators (such as phenolics and monoterpenes) would be revealed. Overall, NDVI associated with yield and vine size. However, the relationships among NDVI and yield components were not as profound as anticipated, which is potentially attributable to saturation phenomena, due to excessive vegetation in the vineyard study blocks particularly later in the growing season. Vine water status demonstrated very inconsistent patterns across blocks and vintages in Cabernet franc and Pinot noir. Strong inverse correlations with the secondary metabolites (i.e. phenolics and monoterpenes) and NDVI were revealed, confirming the rationale that high vigour situations (indicated also by high NDVI) can affect berry composition variables by obstructing phenolic accumulation and coloration, due to restricted sunlight exposure.

Statistical procedures utilised in this thesis (i.e. correlations, PCA, *k*-means clustering and multilinear regression analysis) along with the maps produced for the examined variables intended to determine the nature of the relationships and illustrate the vineyard spatial variability. For this purpose, the results obtained from all these methods are considered satisfactory; correlations established were in good agreement across the statistical methods employed, regardless of the low accounted variability. Previous studies have demonstrated that quadratic regressions were better explaining the relationship among NDVI and pruning weights (Stamatiadis et al. 2006, 2009). Here, when variables were tested for nonlinear relationships, including quadratic regressions, the biological significance (R^2 values) was not enhanced, and in some cases even had negative effect on the dataset. However, more variability may have been explained if fewer variables were included in the datasets; in other PV studies factors mainly include soil composition or water availability. *K*-means clustering classification method revealed (statistically) unique patterns with soil moisture and NDVI, while Moran's *I* spatial autocorrelation index indicated strong clustering patterns among these variables (SM and NDVI). Since both Moran's *I* results and *k*-means showed clustering patterns in NDVI, it is suggested for future studies that sensorial analysis of wines produced from the *k*-means derived NDVI zones might unveil unique differences in wine profiles.

The temporal stability of the spatial patterns for SM and NDVI was depicted on the maps, which is particularly important when vineyards are intended to be divided into sub-blocks of differential biophysical characteristics and productivity. Secondary metabolites (phenolics and terpenes) showed also a high temporal stability across the two vintages. By establishing temporally consistent spatial patterns, information acquired by the use of geospatial technologies can potentially benefit vineyard managers in decision-making processes.

In summary, the usefulness of proximal sensing technology, the GreenSeeker™ in viticultural systems was investigated. The results obtained are considered more than sufficient to support the hypotheses; numerous correlations were revealed among NDVI and other variables along with the good agreement of those. The GreenSeeker™ instrumentation is a tractor-based proximal sensing technology, which offers the growers easier accessibility and applicability along with lower costs in comparison with airborne or spaceborne remote sensing technology, due to the wide mechanisation of viticultural practices (spraying, hedging and mowing). The GreenSeeker™ consists of two active ground-based sensors, which are able to overcome any issues such as shadows, calibration and inter-row spaces, as they have their own source of light. The instrumentation utilised here is a promising precision viticulture tool, which supports the need for a rapid and comprehensive evaluation of grapevine canopy vegetation. Future research is now streamed towards a direct, non-destructive canopy and grape composition assessment tool, as the quality of the final product (i.e. wine) is heavily imposed by grape composition characteristics.

APPENDICES

A. TABLES

Table A 1 General features of Niagara Peninsula Riesling, Cabernet Franc and Pinot noir vineyards used in the study during the 2014 and 2015 vintages.

VINEYARD SITES	LAMBERT FARMS		CAVE SPRING		COYOTE'S RUN	
	Riesling	*Cabernet franc*	*Riesling*	*Cabernet franc*	*Pinot noir EW*	*Pinot noir NS*
VQA Sub-appellation	Four Mile Creek		Beamsville Bench		St. David's Bench	
Area of Vineyard block (ha)	0.81	1.19	2.22	1.54	0.66	0.79
number of sentinel vines	75	77	75	75	84	90
Soil series (Kingston and Presant 1989)	Chinguacousy 19: B=B		Chinguacousy 14; c>B	Chinguacousy 14 (Loamy Phase; CGU.L)	Queenston shale bedrock	
Parent materials	Mainly reddish- hued clay		15-40 cm loamy textures over clay loam till		Reddish- hued clay	
Soil drainage	Imperfect to poor		Imperfect to poor	Imperfect	Imperfect	
Rootstock	SO4		SO4	101-14	SO4	
Vine age at initiation of trial (year planted)	2000		1978	1999	1997/1998	
Vine spacing (m; row X vine)	2.7 X 1.2		2.5 X 1.5	2.7 X 1.44	1.2 X 2.4	
Number of rows; vines per row	15 rows; 2400 vines 160 vines/row		45 rows; 6120 vines 136 vines/row	24 rows 137 vines/row		
Training system	Scott Henry	Guyot	Pendelbogen	Guyot		
Floor management	Alternate sod		Alternate sod	Sod every row		

Table A 2 Average daily minimum temperatures in 2014 and 2015, compared to normal in the three weather stations closer to research sites; St. David's Bench - Coyote's Run winery, NOTL Irvine Road - Lambert vineyards and Lincoln Fly Road - Cave Spring vineyards. Weather data courtesy from www.weatherinnovations.com

	2014							2015						
	Apr	May	June	July	Aug	Sept	Oct	Apr	May	June	July	Aug	Sept	Oct
Normal (St. Catharines EC)	2.1	7.8	13.3	16.4	15.7	11.6	5.6	2.1	7.8	13.3	16.4	15.7	11.6	5.6
St. David's Bench	1.0	8.4	13.7	14.2	14.4	10.5	6.7	2.0	9.3	12.2	14.5	14.5	13.9	5.2
NOTL Irvine Road	1.3	8.0	13.6	15.3	14.9	10.7	7.4	2.4	9.2	12.5	15.3	15.3	13.8	6.4
Lincoln Fly Road	1.0	7.7	13.8	13.4	14.7	11.0	6.5	2.1	9.4	12.0	15.3	15.0	14.0	5.8

Normal
Above-normal
Below-normal

Table A 3 Average daily maximum temperatures in 2014 and 2015, compared to normal in the three weather stations closer to research sites; St. David's Bench - Coyote's Run winery, NOTL Irvine Road - Lambert vineyards and Lincoln Fly Road - Cave Spring vineyards. Weather data courtesy from www.weatherinnovations.com

	2014							2015						
	Apr	May	June	July	Aug	Sept	Oct	Apr	May	June	July	Aug	Sept	Oct
Normal (St. Catharines EC)	12.2	19.4	24.3	27.1	25.9	21.5	14.9	12.2	19.4	24.3	27.1	25.9	21.5	14.9
St. David's Bench	13.3	20.0	26.5	26.5	26.7	23.8	16.8	13.5	23.8	24.0	28.2	26.7	25.5	15.6
NOTL Irvine Road	12.4	19.4	26.0	25.8	25.8	22.8	15.8	12.6	22.9	23.5	27.8	26.3	25.0	15.0
Lincoln Fly Road	11.6	18.8	24.8	25.0	25.0	22.1	15.2	12.1	22.4	22.4	27.1	25.6	24.0	14.3

Normal
Above-normal
Below-normal

Table A4 Basic statistics for yield components, berry composition, and NDVI for the Lambert Cabernet franc vineyard, Virgil, ON, 2014-2015.

*Spread (Bramley 2005) = subtraction minimum from the maximum values, expressed as a % of the median value.

LAMBERT CABERNET FRANC ***(N=77)***							
	Year	**Minimum**	**Maximum**	**Median**	**Mean**	**CV%**	**Spread***
NDVI July	**2014**	0.776	0.815	0.802	0.800	1.07	4.809
	2015	0.765	0.845	0.829	0.827	1.40	9.703
NDVI August	**2014**	0.753	0.826	0.805	0.801	2.16	9.129
	2015	0.698	0.764	0.726	0.729	2.08	9.004
NDVI September	**2014**	0.747	0.818	0.795	0.791	2.11	8.916
	2015	0.658	0.721	0.690	0.691	2.07	9.002
Mean NDVI	**2014**	0.769	0.816	0.799	0.798	1.48	5.919
	2015	0.717	0.772	0.750	0.749	1.43	7.325
Cluster number (per vine)	**2014**	0.0	26.0	9.0	10.1	56.4	288.9
	2015	3.0	90.0	26.0	28.4	54.3	334.6
Yield (kg/vine)	**2014**	0.0	5.1	1.8	1.9	59.7	283.3
	2015	0.4	11.2	4.8	4.9	49.2	227.1
Berry weight (g)	**2014**	147.0	238.7	195.0	193.1	9.1	47.0
	2015	111.0	179.0	146.0	145.8	9.7	46.6
Soluble Solids (°Brix)	**2014**	19.40	23.70	21.90	21.92	3.52	19.63
	2015	12.30	23.10	19.90	19.61	9.29	54.27
pH	**2014**	3.22	3.67	3.55	3.55	1.75	12.68
	2015	3.30	3.66	3.47	3.48	2.46	10.37
Titratable Acidity (g/L)	**2014**	6.80	9.45	7.74	7.81	4.83	34.23
	2015	4.57	8.39	6.93	6.88	9.21	55.12
Anthocyanins (mg/L)	**2014**	584.26	1058.55	792.70	815.93	12.29	59.83
	2015	243.22	917.89	533.24	533.29	24.96	126.52
Colour (au)	**2014**	7.23	14.99	10.68	11.03	16.69	72.66
	2015	4.96	21.49	11.58	12.02	27.93	142.75
Phenols (mg/L)	**2014**	1075.63	2543.46	1799.62	1841.28	20.42	81.56
	2015	771.43	2277.14	1382.14	1363.27	20.82	108.94
Vine size (kg)	**2014**	0.2	1.3	0.6	0.7	34.0	171.9
	2015	0.0	1.4	0.8	0.8	35.9	190.7
January Bud LT_{50}	**2014**	-22.9	-18.8	-20.9	-21.1	-5.5	-19.6
	2015	-24.2	-16.7	-20.3	-20.5	-11.3	-37.1
February Bud LT_{50}	**2014**	-21.6	-18.6	-20.4	-20.1	-4.1	-14.8
	2015	-21.7	-15.1	-17.5	-17.8	-11.4	-37.6
March Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-21.3	-15.7	-17.8	-17.8	-6.8	-31.6
Mean Bud LT_{50}	**2014**	-22.2	-19.0	-20.6	-20.6	-3.4	-15.7
	2015	-21.3	-15.4	-17.9	-18.2	-8.5	-32.9
Soil Moisture July (%)	**2014**	14.9	29.3	20.4	21.2	16.8	70.6
	2015	17.2	30.0	20.6	21.0	12.0	62.5
Soil Moisture August (%)	**2014**	11.3	26.8	18.6	19.0	17.0	83.8
	2015	8.0	22.5	14.4	14.2	15.8	100.7
Soil Moisture September (%)	**2014**	17.4	30.9	21.8	22.0	12.1	62.1
	2015	7.6	30.4	14.6	14.4	30.5	156.7
Mean Soil Moisture (%)	**2014**	15.7	26.3	20.8	20.7	11.8	50.9
	2015	11.6	22.7	16.5	16.5	13.2	66.5
Leaf Water Potential July (Mpa)	**2014**	-1.40	-0.68	-1.15	-1.13	-15.82	-62.61
	2015	-0.87	-0.67	-0.77	-0.77	-7.53	-27.06
Leaf Water Potential August (Mpa)	**2014**	-1.00	-0.55	-0.78	-0.77	-12.72	-58.06
	2015	-1.22	-0.73	-0.99	-0.96	-10.42	-49.24
Leaf Water Potential September (Mpa)	**2014**	-0.95	-0.48	-0.65	-0.67	-17.39	-73.08
	2015	-1.32	-0.62	-0.94	-0.94	-18.56	-73.76
Mean Leaf Water Potential (Mpa)	**2014**	-0.97	-0.68	-0.87	-0.85	-9.75	-33.46
	2015	-1.07	-0.75	-0.88	-0.89	-8.37	-35.72

Table A5 Basic statistics for yield components, berry composition, and NDVI for the Cave Spring Cabernet franc vineyard, Beamsville, ON, 2014-2015.

*Spread (Bramley 2005) = subtraction minimum from the maximum values, expressed as a % of the median value.

CAVE SPRING CABERNET FRANC ***(N=75)***							
	Year	**Minimum**	**Maximum**	**Median**	**Mean**	**CV%**	**Spread***
NDVI July	**2014**	0.784	0.834	0.811	0.812	1.39	6.237
	2015	0.838	0.874	0.861	0.859	0.84	4.188
NDVI August	**2014**	0.741	0.832	0.787	0.786	2.55	11.590
	2015	0.774	0.821	0.805	0.802	1.29	5.814
NDVI September	**2014**	0.690	0.823	0.768	0.767	3.69	17.322
	2015	0.771	0.819	0.795	0.797	1.38	5.962
Mean NDVI	**2014**	0.745	0.829	0.786	0.788	2.30	10.777
	2015	0.800	0.833	0.820	0.819	0.95	3.985
Cluster number (per vine)	**2014**	8.0	51.0	22.0	22.1	28.9	195.5
	2015	7.0	32.0	23.0	21.9	25.2	108.7
Yield (kg/vine)	**2014**	1.3	7.7	3.5	3.6	29.4	182.9
	2015	1.3	5.9	3.3	3.3	25.4	139.6
Berry weight (g)	**2014**	107.8	212.3	171.2	169.7	11.1	61.1
	2015	99.0	182.0	130.0	129.9	9.8	63.8
Soluble Solids (°Brix)	**2014**	18.50	25.50	23.40	23.23	5.11	29.91
	2015	18.00	25.60	24.20	23.90	4.69	31.40
pH	**2014**	3.21	3.55	3.41	3.40	2.10	9.97
	2015	3.24	3.55	3.42	3.42	1.79	9.06
Titratable Acidity (g/L)	**2014**	7.06	10.37	8.02	8.04	6.94	41.27
	2015	5.94	7.68	6.88	6.90	4.90	25.29
Anthocyanins (mg/L)	**2014**	638.99	1345.63	872.11	888.76	13.70	81.03
	2015	390.02	1279.01	954.71	952.40	16.75	93.12
Colour (au)	**2014**	6.51	20.48	11.54	11.87	20.00	121.12
	2015	8.13	28.99	21.25	20.90	20.43	98.16
Phenols (mg/L)	**2014**	1076.00	3000.00	1720.00	1707.19	20.68	111.86
	2015	1017.14	2494.29	1836.43	1820.10	17.64	80.44
Vine size (kg)	**2014**	0.4	1.5	0.8	0.9	22.9	132.5
	2015	0.5	1.7	1.0	1.0	24.5	125.0
January Bud LT_{50}	**2014**	-22.2	-17.7	-19.5	-19.7	-7.2	-22.9
	2015	-21.3	-15.9	-17.8	-18.1	-7.7	-30.6
February Bud LT_{50}	**2014**	-21.7	-16.9	-19.4	-19.2	-6.6	-24.9
	2015	-20.2	-17.0	-18.0	-18.3	-5.5	-17.3
March Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-17.8	-14.8	-16.4	-16.3	-5.1	-18.3
Mean Bud LT_{50}	**2014**	-21.7	-17.3	-19.4	-19.5	-6.6	-22.9
	2015	-18.8	-16.5	-17.5	-17.5	-4.2	-13.3
Soil Moisture July (%)	**2014**	13.0	36.1	20.7	20.6	35.4	111.9
	2015	23.2	42.4	32.0	33.0	12.9	60.0
Soil Moisture August (%)	**2014**	13.6	26.0	19.0	19.1	14.5	65.3
	2015	12.9	29.0	18.6	18.7	16.4	86.6
Soil Moisture September (%)	**2014**	13.1	29.8	22.2	21.5	17.2	75.5
	2015	16.9	35.7	25.9	25.8	16.5	72.6
Mean Soil Moisture (%)	**2014**	12.6	28.3	20.4	20.4	17.2	77.4
	2015	20.6	31.6	25.6	25.8	9.4	43.1
Leaf Water Potential July (Mpa)	**2014**	-1.08	-0.68	-0.88	-0.87	-12.87	-46.67
	2015	-0.76	-0.50	-0.60	-0.62	-11.95	-44.17
Leaf Water Potential August (Mpa)	**2014**	-1.10	-0.78	-0.85	-0.89	-12.21	-38.24
	2015	-1.36	-1.08	-1.22	-1.22	-7.02	-22.95
Leaf Water Potential September (Mpa)	**2014**	-1.48	-0.73	-1.08	-1.12	-21.14	-69.77
	2015	-1.63	-1.18	-1.51	-1.49	-7.26	-29.57
Mean Leaf Water Potential (Mpa)	**2014**	-1.15	-0.75	-0.95	-0.96	-12.11	-42.11
	2015	-1.20	-0.93	-1.13	-1.11	-5.91	-23.72

Table A6 Basic statistics for yield components, berry composition, and NDVI for the Coyote's Run (East-West) vineyard, St. David's, ON, 2014-2015.

*Spread (Bramley 2005) = subtraction minimum from the maximum values, expressed as a % of the median value.

COYOTE'S RUN PINOT NOIR (E-W) ***(N=84)***							
	Year	**Minimum**	**Maximum**	**Median**	**Mean**	**CV%**	**Spread***
NDVI July	**2014**	0.740	0.830	0.796	0.797	2.15	11.374
	2015	0.612	0.776	0.749	0.741	4.20	21.816
NDVI August	**2014**	0.742	0.838	0.805	0.800	2.64	11.902
	2015	0.412	0.779	0.753	0.743	6.40	48.737
NDVI September	**2014**	0.632	0.789	0.755	0.750	2.94	20.822
	2015	0.681	0.822	0.793	0.791	2.25	17.790
Mean NDVI	**2014**	0.736	0.815	0.784	0.782	2.17	10.040
	2015	0.628	0.784	0.766	0.758	3.27	20.358
Cluster number (per vine)	**2014**	1.0	38.0	14.0	15.5	49.3	264.3
	2015	0.0	27.0	12.0	12.4	53.7	225.0
Yield (kg/vine)	**2014**	0.1	5.1	1.4	1.5	62.8	357.1
	2015	0.0	2.8	0.9	1.0	59.7	319.3
Berry weight (g)	**2014**	94.2	177.7	150.6	148.3	11.1	55.5
	2015	85.0	167.0	125.0	122.9	12.9	65.6
Soluble Solids (°Brix)	**2014**	18.50	24.00	20.90	20.88	6.13	26.32
	2015	17.30	27.70	21.95	21.93	8.10	47.38
pH	**2014**	3.36	3.78	3.63	3.62	2.47	11.57
	2015	3.38	4.02	3.72	3.71	3.23	17.23
Titratable Acidity (g/L)	**2014**	7.72	12.04	9.43	9.48	8.51	45.84
	2015	5.59	9.96	6.82	7.03	12.30	64.08
Anthocyanins (mg/L)	**2014**	306.39	533.24	415.08	414.77	13.40	54.65
	2015	161.12	603.57	399.87	393.76	18.96	110.65
Colour (au)	**2014**	3.51	8.81	5.38	5.44	16.21	98.50
	2015	2.26	9.44	7.17	6.95	18.20	100.14
Phenols (mg/L)	**2014**	1194.64	2712.06	1606.23	1670.83	17.49	94.47
	2015	703.57	2126.43	1506.79	1424.97	26.16	94.43
Vine size (kg)	**2014**	0.2	1.0	0.6	0.6	30.6	145.5
	2015	0.0	1.1	0.7	0.7	38.9	154.7
January Bud LT_{50}	**2014**	-25.1	-17.4	-21.3	-21.4	-8.1	-36.2
	2015	-25.4	-16.4	-20.6	-20.6	-10.2	-43.6
February Bud LT_{50}	**2014**	-22.6	-18.4	-21.2	-21.0	-5.1	-20.1
	2015	-20.0	-12.4	-18.0	-17.7	-9.7	-41.9
March Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-17.6	-15.0	-16.0	-16.2	-4.7	-16.1
Mean Bud LT_{50}	**2014**	-23.5	-19.0	-21.1	-21.2	-5.0	-21.5
	2015	-20.1	-16.7	-18.2	-18.1	-4.8	-18.3
Soil Moisture July (%)	**2014**	12.3	32.5	20.2	20.4	20.1	99.6
	2015	13.4	34.9	24.6	23.9	17.7	87.2
Soil Moisture August (%)	**2014**	7.4	33.8	19.9	19.5	26.8	132.5
	2015	12.3	30.2	20.5	20.6	18.9	87.4
Soil Moisture September (%)	**2014**	9.0	30.1	20.5	20.3	21.4	103.2
	2015	12.1	35.6	20.5	21.2	24.0	114.4
Mean Soil Moisture (%)	**2014**	9.8	30.0	20.0	20.1	19.6	101.0
	2015	12.7	32.4	22.1	21.9	17.0	89.2
Leaf Water Potential July (Mpa)	**2014**	-1.05	-0.68	-0.80	-0.81	-11.44	-46.88
	2015	-1.00	-0.64	-0.78	-0.80	-12.89	-47.10
Leaf Water Potential August (Mpa)	**2014**	-1.13	-0.58	-0.93	-0.90	-16.85	-59.46
	2015	-1.21	-0.91	-1.03	-1.03	-8.17	-29.13
Leaf Water Potential September (Mpa)	**2014**	-0.88	-0.58	-0.73	-0.72	-11.66	-41.38
	2015	-1.13	-0.68	-0.84	-0.85	-16.39	-53.57
Mean Leaf Water Potential (Mpa)	**2014**	-0.93	-0.68	-0.82	-0.81	-6.85	-30.61
	2015	-1.10	-0.74	-0.88	-0.89	-9.51	-40.23

Table A7 Basic statistics for yield components, berry composition, and NDVI for the Coyote's Run (North-South) vineyard, St. David's, ON, 2014-2015.

*Spread (Bramley 2005) = subtraction minimum from the maximum values, expressed as a % of the median value.

COYOTE'S RUN PINOT NOIR (N-S) (N= 90)							
	Year	**Minimum**	**Maximum**	**Median**	**Mean**	**CV%**	**Spread***
NDVI July	**2014**	0.693	0.852	0.818	0.819	2.81	19.417
	2015	0.743	0.799	0.777	0.775	1.71	7.221
NDVI August	**2014**	0.772	0.858	0.810	0.813	2.21	10.531
	2015	0.741	0.790	0.772	0.771	1.25	6.407
NDVI September	**2014**	0.755	0.845	0.800	0.802	2.24	11.139
	2015	0.791	0.849	0.815	0.815	1.10	7.131
Mean NDVI	**2014**	0.762	0.850	0.808	0.811	2.03	10.857
	2015	0.771	0.803	0.787	0.787	1.06	4.034
Cluster number (per vine)	**2014**	4.0	55.0	16.0	17.6	50.5	318.8
	2015	0.0	34.0	14.0	14.2	49.5	242.9
Yield (kg/vine)	**2014**	0.3	5.8	1.7	1.8	53.0	323.5
	2015	0.0	3.2	1.0	1.1	56.6	326.4
Berry weight (g)	**2014**	97.0	176.3	141.9	141.6	10.7	55.9
	2015	90.0	172.0	127.0	128.4	10.8	64.6
Soluble Solids (°Brix)	**2014**	17.80	25.00	22.85	22.69	4.75	31.51
	2015	21.00	29.90	24.40	24.64	7.88	36.48
pH	**2014**	3.33	3.78	3.57	3.57	2.65	12.62
	2015	3.56	4.16	3.81	3.79	2.40	15.77
Titratable Acidity (g/L)	**2014**	7.09	9.68	8.39	8.40	5.84	30.89
	2015	5.38	8.64	6.20	6.27	8.35	52.62
Anthocyanins (mg/L)	**2014**	244.75	554.47	400.50	402.22	14.06	77.33
	2015	186.70	603.57	388.61	380.44	14.37	107.27
Colour (au)	**2014**	3.42	8.36	5.30	5.44	15.44	93.24
	2015	4.71	9.01	6.42	6.52	14.19	67.03
Phenols (mg/L)	**2014**	936.78	2275.68	1611.19	1607.11	18.43	83.10
	2015	614.29	2312.86	1523.21	1582.99	23.97	111.51
Vine size (kg)	**2014**	0.1	0.9	0.3	0.3	38.2	246.7
	2015	0.0	1.6	0.7	0.7	36.7	224.6
January Bud LT_{50}	**2014**	-24.3	-18.1	-22.2	-21.7	-8.5	-27.8
	2015	-22.3	-15.8	-20.0	-19.7	-8.6	-32.6
February Bud LT_{50}	**2014**	-21.4	-17.5	-20.2	-20.0	-5.5	-19.2
	2015	-20.1	-15.5	-17.8	-17.7	-7.5	-26.1
March Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-18.1	-14.0	-16.2	-16.1	-6.4	-24.9
Mean Bud LT_{50}	**2014**	-22.4	-18.4	-20.8	-20.8	-5.9	-19.2
	2015	-19.3	-16.2	-17.5	-17.5	-4.7	-17.8
Soil Moisture July (%)	**2014**	15.1	33.3	24.4	24.3	16.2	74.7
	2015	18.1	34.2	26.1	26.1	14.2	61.6
Soil Moisture August (%)	**2014**	16.4	31.0	23.7	23.2	14.3	61.6
	2015	16.7	31.5	22.9	22.9	13.5	64.7
Soil Moisture September (%)	**2014**	18.4	33.5	24.2	24.5	13.2	62.5
	2015	15.1	31.4	20.7	20.9	15.2	78.7
Mean Soil Moisture (%)	**2014**	18.3	30.4	23.8	24.0	11.1	51.1
	2015	17.7	29.2	23.4	23.3	11.2	49.0
Leaf Water Potential July (Mpa)	**2014**	-1.10	-0.68	-0.80	-0.83	-12.69	-53.13
	2015	-0.95	-0.68	-0.79	-0.80	-8.28	-34.70
Leaf Water Potential August (Mpa)	**2014**	-1.05	-0.70	-0.83	-0.86	-11.66	-42.42
	2015	-1.22	-0.85	-1.06	-1.05	-10.68	-35.07
Leaf Water Potential September (Mpa)	**2014**	-0.98	-0.65	-0.80	-0.81	-10.21	-40.63
	2015	-1.36	-0.83	-0.99	-1.04	-15.42	-53.03
Mean Leaf Water Potential (Mpa)	**2014**	-1.01	-0.72	-0.85	-0.84	-6.91	-34.31
	2015	-1.08	-0.87	-0.94	-0.96	-6.41	-22.50

Table A8 Basic statistics for yield components, berry composition, and NDVI for the Cave Spring Riesling vineyard, Beamsville, ON, 2014-2015.

*Spread (Bramley 2005) = subtraction minimum from the maximum values, expressed as a % of the median value

CAVE SPRING RIESLING (N=75)							
	Year	Minimum	Maximum	Median	Mean	CV%	Spread*
NDVI July	2014	0.768	0.818	0.802	0.801	1.25	6.162
	2015	0.780	0.856	0.841	0.834	2.03	9.071
NDVI August	2014	0.748	0.835	0.804	0.802	1.96	10.862
	2015	0.722	0.802	0.778	0.774	2.27	10.289
NDVI September	2014	0.722	0.811	0.781	0.778	2.58	11.474
	2015	0.727	0.804	0.777	0.775	2.10	9.925
Mean NDVI	2014	0.764	0.813	0.795	0.793	1.52	6.136
	2015	0.743	0.816	0.798	0.795	1.70	9.165
Cluster number (per vine)	2014	7.0	47.0	30.0	28.6	28.9	133.3
	2015	14.0	46.0	29.0	29.2	19.9	110.3
Yield (kg/vine)	2014	1.2	9.1	5.4	5.1	33.2	146.3
	2015	2.4	7.4	4.9	4.9	23.5	102.9
Berry weight (g)	2014	175.1	248.9	199.8	201.8	7.3	36.9
	2015	119.0	206.0	165.0	167.4	10.5	52.7
Soluble Solids (°Brix)	2014	15.3	21.9	20.0	19.9	5.7	33.0
	2015	14.0	22.8	19.5	19.4	6.4	45.1
pH	2014	3.09	3.40	3.22	3.22	1.94	9.63
	2015	3.05	3.41	3.20	3.19	1.95	11.25
Titratable Acidity (g/L)	2014	8.20	12.40	10.34	10.38	8.54	40.62
	2015	6.92	11.11	9.64	9.65	7.95	43.46
Free Volatile Terpenes (FVT) (mg/L)	2014	0.22	0.46	0.35	0.34	17.91	67.20
	2015	0.23	0.63	0.37	0.42	29.40	106.78
Potentially-Volatile Terpenes (PVT) (mg/L)	2014	1.21	1.91	1.47	1.49	15.55	47.58
	2015	1.33	2.81	1.88	1.93	16.44	79.05
Vine size (kg)	2014	0.3	1.5	0.8	0.8	27.4	150.6
	2015	0.4	1.5	0.9	0.8	26.5	128.2
January Bud LT_{50}	2014	-24.4	-18.7	-20.4	-20.9	-7.8	-27.8
	2015	-22.9	-10.2	-19.8	-19.4	-14.2	-64.0
February Bud LT_{50}	2014	-23.4	-19.4	-21.2	-21.1	-5.3	-18.5
	2015	-21.8	-17.5	-20.1	-19.9	-5.3	-21.0
March Bud LT_{50}	2014	--	--	--	--	--	--
	2015	-19.7	-15.3	-18.2	-18.0	-5.5	-24.2
Mean Bud LT_{50}	2014	-22.5	-19.4	-21.3	-21.0	-4.7	-14.3
	2015	-20.6	-16.1	-19.2	-19.1	-5.6	-23.6
Soil Moisture July (%)	2014	4.0	28.1	18.6	18.6	29.5	129.8
	2015	19.5	41.4	27.5	27.8	15.4	80.0
Soil Moisture August (%)	2014	12.8	24.7	18.6	18.9	14.1	64.0
	2015	14.0	31.6	19.8	20.1	19.2	89.1
Soil Moisture September (%)	2014	12.9	26.1	18.5	18.5	14.1	71.4
	2015	13.3	30.5	19.6	20.4	18.7	88.0
Mean Soil Moisture (%)	2014	11.8	24.0	18.6	18.7	13.5	65.4
	2015	16.7	30.3	22.5	22.8	13.0	60.2
Leaf Water Potential July (Mpa)	2014	-0.93	-0.63	-0.73	-0.74	-11.47	-41.38
	2015	-0.67	-0.41	-0.50	-0.51	-12.87	-52.53
Leaf Water Potential August (Mpa)	2014	-0.88	-0.53	-0.70	-0.72	-15.14	-50.00
	2015	-1.09	-0.65	-0.81	-0.85	-14.37	-54.66
Leaf Water Potential September (Mpa)	2014	-1.33	-0.70	-1.08	-1.06	-17.22	-58.14
	2015	-1.41	-1.02	-1.31	-1.26	-10.46	-29.89
Mean Leaf Water Potential (Mpa)	2014	-1.02	-0.64	-0.86	-0.84	-12.64	-43.69
	2015	-1.02	-0.74	-0.89	-0.87	-10.39	-31.33

Table A9 Basic statistics for yield components, berry composition, and NDVI for the Lambert Riesling vineyard, Virgil, ON, 2014-2015.

*Spread (Bramley 2005) = subtraction minimum from the maximum values, expressed as a % of the median value. **--** Vine size samples collected in 2015 only.

LAMBERT RIESLING ***(N=75)***							
	Year	**Minimum**	**Maximum**	**Median**	**Mean**	**CV%**	**Spread***
NDVI July	**2014**	0.776	0.814	0.797	0.797	1.06	4.771
	2015	0.809	0.843	0.829	0.828	0.92	4.115
NDVI August	**2014**	0.752	0.807	0.787	0.786	1.60	6.937
	2015	0.748	0.796	0.772	0.773	1.52	6.251
NDVI September	**2014**	0.726	0.792	0.767	0.765	1.82	8.576
	2015	0.717	0.765	0.744	0.745	1.56	6.545
Mean NDVI	**2014**	0.757	0.802	0.785	0.783	1.37	5.738
	2015	0.773	0.797	0.787	0.787	0.74	3.136
Cluster number (per vine)	**2014**	13.0	129.0	35.0	42.5	55.5	331.4
	2015	2.0	93.0	34.0	36.2	52.1	267.6
Yield (kg/vine)	**2014**	1.7	10.2	4.9	5.3	36.3	173.5
	2015	0.3	10.5	3.9	4.3	44.1	260.2
Berry weight (g)	**2014**	137.5	234.2	191.1	190.1	9.7	50.6
	2015	128.0	198.0	165.0	162.6	9.7	42.4
Soluble Solids (°Brix)	**2014**	15.5	22.0	19.6	19.5	6.8	33.2
	2015	10.9	22.4	19.5	19.1	9.2	59.0
pH	**2014**	3.05	3.46	3.28	3.28	2.54	12.50
	2015	3.16	3.62	3.37	3.37	2.38	13.65
Titratable Acidity (g/L)	**2014**	8.89	12.80	10.37	10.42	8.67	37.70
	2015	6.06	10.81	8.33	8.49	10.52	57.02
Free Volatile Terpenes (FVT) (mg/L)	**2014**	0.27	0.48	0.35	0.36	15.84	59.20
	2015	0.38	0.89	0.65	0.64	23.58	79.41
Potentially-Volatile Terpenes (PVT) (mg/L)	**2014**	0.90	2.07	1.61	1.59	17.84	73.36
	2015	1.50	3.99	2.65	2.57	24.98	94.26
Vine size (kg)	**2014**	--	--	--	--	--	--
	2015	0.3	1.5	0.8	0.8	25.6	146.3
January Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-24.9	-15.5	-19.8	-20.3	-14.0	-47.3
February Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-22.9	-16.6	-19.5	-19.5	-7.7	-32.1
March Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-19.4	-15.6	-17.5	-17.6	-5.9	-21.7
Mean Bud LT_{50}	**2014**	--	--	--	--	--	--
	2015	-20.7	-16.4	-19.1	-19.0	-6.0	-22.5
Soil Moisture July (%)	**2014**	16.1	32.2	21.8	22.5	15.9	74.2
	2015	19.3	31.8	25.3	25.4	11.3	49.3
Soil Moisture August (%)	**2014**	14.4	29.0	21.8	21.8	13.9	67.4
	2015	11.2	24.0	18.3	18.2	12.3	69.9
Soil Moisture September (%)	**2014**	19.1	30.6	24.2	24.0	11.2	47.6
	2015	12.7	25.5	17.7	17.6	13.5	72.3
Mean Soil Moisture (%)	**2014**	17.6	28.4	22.6	22.8	9.5	47.9
	2015	16.1	25.9	20.4	20.4	10.1	48.0
Leaf Water Potential July (Mpa)	**2014**	-1.05	-0.70	-0.88	-0.87	-10.73	-40.00
	2015	-0.64	-0.43	-0.51	-0.51	-11.91	-41.18
Leaf Water Potential August (Mpa)	**2014**	-1.00	-0.68	-0.83	-0.83	-10.80	-39.39
	2015	-1.07	-0.55	-0.82	-0.81	-12.52	-63.06
Leaf Water Potential September (Mpa)	**2014**	-0.98	-0.58	-0.73	-0.74	-15.97	-55.17
	2015	-1.34	-0.75	-0.98	-1.00	-15.62	-60.00
Mean Leaf Water Potential (Mpa)	**2014**	-0.92	-0.70	-0.80	-0.82	-7.62	-27.08
	2015	-0.90	-0.60	-0.78	-0.78	-9.66	-37.98

Table A10 *p*-value correlation matrix for Lambert Cabernet franc 2014.

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	0.747	0.079	**0.002**	0.692	0.251	0.596	0.141	0.865	0.377	0.055	0.622	0.844	0.885	**0.003**	0.403	0.067	**0.013**	0.630	0.717	0.122	0.930	**0.036**	0.369	0.243	**0.032**
NDVI August		**0**	**< 0.0001**	**< 0.0001**	0.405	0.899	0.559	**0.049**	0.108	**0.034**	0.451	0.624	**0.004**	0.381	0.434	0.278	0.994	0.378	0.309	0.856	0.346	0.514	**0.001**	0.641	0.052	**0.032**
NDVI September			**0**	**< 0.0001**	0.308	0.553	0.315	**0.031**	0.094	**0.031**	0.482	0.499	**0.003**	0.132	0.114	0.084	0.782	0.497	0.228	0.745	0.328	0.695	**0.008**	0.736	0.251	0.216
Mean NDVI				**0**	0.326	0.535	0.376	**0.019**	0.108	**0.023**	0.245	0.499	**0.006**	0.243	0.067	0.122	0.563	0.882	0.347	0.879	0.589	0.601	**0.022**	0.880	0.233	0.275
Cluster number					**0**	**< 0.0001**	0.098	0.674	**0.023**	0.621	0.471	0.424	0.307	0.109	0.328	0.828	0.506	0.343	0.472	0.304	0.250	0.852	0.692	0.118	0.457	0.898
Yield (kg/vine)						**0**	**0.045**	0.896	**0.020**	0.790	0.915	0.976	0.495	0.059	0.103	0.277	0.495	0.498	0.193	0.213	0.176	0.767	0.404	**0.027**	0.119	**0.000**
Berry weight (g)							**0**	0.194	0.868	0.487	0.920	0.250	0.395	0.132	0.238	0.342	0.131	0.121	0.098	0.346	0.068	0.587	0.286	0.873	0.380	0.168
Soluble Solids (°Brix)								**0**	0.053	0.264	**< 0.0001**	**0.003**	0.439	0.067	0.582	0.594	0.891	0.798	0.308	0.107	0.249	0.217	0.930	0.987	0.408	0.390
pH									**0**	**< 0.0001**	0.968	**0.015**	0.741	0.088	0.180	0.193	0.740	0.679	0.714	0.692	0.825	0.326	0.603	0.351	0.182	0.839
Titratable Acidity (g/L)										**0**	0.783	0.097	0.825	0.393	0.117	0.229	0.571	0.585	0.756	0.217	0.755	0.571	0.952	0.936	0.679	0.462
Anthocyanins (mg/L)											**0**	**< 0.0001**	**0.023**	0.137	0.338	0.437	0.746	**0.029**	**0.012**	**0.022**	**0.002**	0.066	0.378	0.896	0.087	0.135
Colour (au)												**0**	0.741	0.570	0.365	0.426	0.232	0.365	0.114	0.303	0.131	0.418	0.988	0.259	0.275	0.056
Phenols (mg/L)													**0**	0.822	0.078	0.067	0.715	0.511	0.796	0.481	0.492	0.324	0.896	0.810	0.525	0.490
Vine size (kg)														**0**	0.392	0.064	0.714	0.432	0.176	0.627	0.701	0.479	0.468	0.490	0.593	0.598
January Bud LT_{50}															**0**	0.920	**< 0.0001**	0.303	0.111	0.156	0.483	**0.045**	**< 0.0001**	0.900	**0.002**	**0.024**
February Bud LT_{50}																**0**	**< 0.0001**	**0.003**	0.953	0.774	0.179	0.412	**0.004**	0.122	0.852	**0.043**
Mean Bud LT_{50}																	**0**	**0.010**	0.211	0.189	0.838	0.256	**< 0.0001**	0.432	**0.017**	0.520
Soil Moisture July (%)																		**0**	**0.010**	**0.035**	**< 0.0001**	0.211	**< 0.0001**	0.327	**0.045**	0.946
Soil Moisture August (%)																			**0**	**< 0.0001**	**< 0.0001**	0.386	0.347	0.909	0.353	0.286
Soil Moisture September (%)																				**0**	**< 0.0001**	0.694	0.816	0.111	0.716	0.902
Mean Soil Moisture (%)																					**0**	0.257	**0.013**	0.272	0.212	0.586
Leaf Water Potential July (MPa)																						**0**	**< 0.0001**	0.084	**< 0.0001**	0.457
Leaf Water Potential August (MPa)																							**0**	0.097	**< 0.0001**	0.095
Leaf Water Potential September (MPa)																								**0**	**0.033**	0.137
Mean Leaf Water Potential (MPa)																									**0**	0.060
Cluster weight (kg)																										**0**

Table A11 *p*-value correlation matrix for Lambert Cabernet franc 2015

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	March Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	0.505	0.358	**0.000**	0.829	0.797	0.651	0.565	0.355	0.478	0.473	0.655	0.828	0.733	0.275	0.992	0.227	0.878	0.338	0.072	0.595	0.535	**0.006**	**0.001**	0.221	0.078	0.686
NDVI August		**0**	**< 0.0001**	**< 0.0001**	0.546	0.638	0.752	0.060	0.057	0.504	0.095	**0.032**	0.771	0.142	0.788	0.416	0.902	0.626	0.079	0.522	0.774	0.487	**0.001**	**0.028**	**0.007**	0.782	0.683
NDVI September			**0**	**< 0.0001**	0.162	0.311	0.258	**0.005**	**0.002**	0.299	0.075	**0.010**	0.803	0.218	0.975	0.939	0.627	0.906	0.144	0.237	0.825	0.266	**0.007**	0.177	**0.012**	0.528	0.214
Mean NDVI				**0**	0.408	0.562	0.625	0.055	**0.008**	0.301	0.189	**0.021**	0.917	0.265	0.726	0.682	0.597	0.845	0.261	0.855	0.877	0.550	**0.000**	0.678	**0.005**	0.296	0.373
Cluster number					**0**	**< 0.0001**	**0.012**	**0.018**	**< 0.0001**	**0.008**	0.779	0.447	0.907	**0.002**	0.715	0.176	0.206	0.192	0.471	0.343	0.269	0.431	0.390	0.679	0.812	0.553	**0.016**
Yield (kg/vine)						**0**	0.169	0.145	**0.000**	**0.031**	0.660	0.873	0.980	**< 0.0001**	0.806	0.132	0.152	0.287	0.856	0.214	0.193	0.220	0.335	0.672	0.833	0.785	0.682
Berry weight (g)							**0**	**0.046**	0.089	0.094	0.338	0.954	0.872	0.155	**0.042**	0.426	0.190	**0.046**	0.629	0.886	0.920	0.763	0.823	0.528	0.418	0.329	**0.001**
Soluble Solids (°Brix)								**0**	**0.011**	0.054	0.272	0.140	0.277	0.877	0.107	0.900	0.882	0.413	0.935	0.080	0.646	0.800	0.482	0.968	0.377	0.598	**0.020**
pH									**0**	**< 0.0001**	0.648	**0.002**	0.210	0.850	0.886	0.345	0.350	0.388	**0.047**	0.090	**0.007**	0.110	0.309	0.847	0.412	0.320	**0.012**
Titratable Acidity (g/L)										**0**	0.700	**0.000**	0.738	0.910	0.241	0.592	0.753	0.817	**0.006**	0.720	0.765	0.344	0.438	0.751	0.805	0.893	0.109
Anthocyanins (mg/L)											**0**	**< 0.0001**	**< 0.0001**	0.552	0.620	0.847	0.689	0.617	0.197	0.615	**0.013**	**0.019**	0.127	0.910	0.676	0.440	0.805
Colour (au)												**0**	**< 0.0001**	0.305	0.807	0.271	0.662	0.588	0.483	0.693	**0.003**	0.068	**0.005**	0.806	0.952	0.521	**0.042**
Phenols (mg/L)													**0**	0.263	0.394	0.945	0.389	0.471	0.199	0.189	**0.002**	0.261	0.340	0.545	**0.002**	**0.003**	0.983
Vine size (kg)														**0**	0.269	0.445	0.859	0.887	0.196	0.227	0.240	0.088	0.639	0.824	0.345	0.605	**0.046**
January Bud LT_{50}															**0**	0.522	0.314	**0.007**	0.398	0.063	0.980	0.285	0.102	0.975	0.844	0.808	0.230
February Bud LT_{50}																**0**	0.295	**0.012**	0.152	0.401	0.254	0.723	0.859	0.238	0.473	0.832	0.780
March Bud LT_{50}																	**0**	**0.016**	0.713	0.124	0.704	0.572	0.551	0.783	0.986	0.971	0.526
Mean Bud LT_{50}																		**0**	0.732	**0.042**	0.492	0.345	0.339	0.640	0.649	0.968	0.799
Soil Moisture July (%)																			**0**	**< 0.0001**	0.853	**< 0.0001**	0.644	0.969	0.079	0.131	0.053
Soil Moisture August (%)																				**0**	**0.000**	**< 0.0001**	0.232	0.586	0.973	0.969	0.475
Soil Moisture September (%)																					**0**	**< 0.0001**	0.640	0.922	0.059	0.121	0.353
Mean Soil Moisture (%)																						**0**	0.786	0.916	0.552	0.658	0.107
Leaf Water Potential July (MPa)																							**0**	0.892	0.818	**0.031**	0.768
Leaf Water Potential August (MPa)																								**0**	0.118	**< 0.0001**	0.558
Leaf Water Potential September (MPa)																									**0**	**< 0.0001**	0.247
Mean Leaf Water Potential (MPa)																										**0**	0.275
Cluster weight (kg)																											**0**

Table A12 *p*-value correlation matrix for Cave Spring Cabernet franc 2014

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.000**	**0.000**	**0.000**	0.595	0.240	0.543	**0.000**	**0.009**	0.121	**0.000**	**0.000**	**0.000**	**0.000**	0.195	0.117	0.138	0.076	0.699	0.131	0.070	**0.020**	0.643	0.911	0.420	**0.000**
NDVI August		**0**	**< 0.0001**	**< 0.0001**	0.522	0.432	0.790	**0.038**	0.121	0.804	**0.000**	**0.013**	**0.007**	**0.007**	0.554	0.373	0.446	0.177	0.100	0.092	**0.038**	**0.016**	0.243	0.760	0.182	**0.001**
NDVI September			**0**	**< 0.0001**	0.971	0.212	0.634	0.058	0.100	0.693	**0.001**	**0.013**	**0.000**	**0.000**	0.592	0.784	0.667	0.220	0.109	0.313	0.099	0.368	0.760	0.514	0.953	**0.005**
Mean NDVI				**0**	0.715	0.236	0.825	**0.011**	**0.049**	0.537	**< 0.0001**	**0.002**	**0.000**	**0.000**	0.443	0.427	0.417	0.132	0.128	0.144	**0.045**	0.067	0.493	0.802	0.531	**0.000**
Cluster number					**0**	**< 0.0001**	0.200	0.080	**0.003**	0.917	0.769	0.627	0.518	0.721	0.739	0.518	0.617	0.479	0.297	0.152	0.675	0.180	0.609	**0.031**	**0.040**	**0.017**
Yield (kg/vine)						**0**	0.669	**0.002**	**0.008**	0.578	0.081	**0.046**	**0.030**	**0.017**	0.358	0.652	0.467	0.596	0.550	0.465	0.881	0.496	0.540	0.152	0.166	**0.049**
Berry weight (g)							**0**	**0.002**	0.573	0.199	**0.000**	**< 0.0001**	0.060	**0.027**	0.730	0.794	0.950	**0.020**	0.279	**0.010**	**0.019**	0.086	0.830	0.812	0.522	**0.001**
Soluble Solids (°Brix)								**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0.000**	0.050	0.453	0.193	0.294	0.083	0.227	0.568	**0.041**	**0.037**	0.606	0.211	0.980	**0.011**
pH									**0**	**0.001**	**0.003**	0.276	0.309	0.102	0.067	**0.012**	**0.025**	0.171	0.445	0.915	0.183	0.082	0.487	0.077	0.395	0.712
Titratable Acidity (g/L)										**0**	**0.001**	**0.002**	0.121	0.525	0.540	0.051	0.197	**0.005**	0.115	0.624	**0.010**	0.098	0.774	**0.001**	0.137	0.274
Anthocyanins (mg/L)											**0**	**< 0.0001**	**< 0.0001**	**0.006**	0.277	0.123	0.175	**0.046**	0.562	**0.022**	**0.010**	**0.002**	0.096	0.540	0.054	**0.006**
Colour (au)												**0**	**< 0.0001**	**0.002**	0.259	0.072	0.133	0.087	0.148	**0.008**	**0.002**	0.394	0.609	0.227	0.482	**0.002**
Phenols (mg/L)													**0**	**0.000**	0.230	0.375	0.273	0.122	0.817	0.695	0.307	0.152	**0.018**	**0.016**	**0.004**	**0.014**
Vine size (kg)														**0**	0.153	0.244	0.174	0.143	0.083	**0.004**	0.099	0.979	**0.044**	0.102	0.081	**< 0.0001**
January Bud LT_{50}															**0**	**< 0.0001**	**< 0.0001**	0.330	0.456	0.719	0.436	0.173	0.051	0.546	0.807	0.362
February Bud LT_{50}																**0**	**< 0.0001**	**0.039**	**0.039**	0.120	**0.012**	**0.018**	0.644	0.511	0.876	0.745
Mean Bud LT_{50}																	**0**	0.122	0.157	0.339	0.099	0.057	0.195	0.991	0.833	0.732
Soil Moisture July (%)																		**0**	**0.017**	**0.001**	**< 0.0001**	**0.016**	0.275	**0.020**	0.647	0.585
Soil Moisture August (%)																			**0**	0.104	**< 0.0001**	0.059	0.202	0.685	0.471	0.679
Soil Moisture September (%)																				**0**	**< 0.0001**	**0.027**	0.551	0.196	0.076	0.076
Mean Soil Moisture (%)																					**0**	**0.002**	0.176	0.237	0.544	0.302
Leaf Water Potential July (MPa)																						**0**	**< 0.0001**	**0.006**	**< 0.0001**	0.152
Leaf Water Potential August (MPa)																							**0**	0.086	**< 0.0001**	0.664
Leaf Water Potential September (MPa)																								**0**	**< 0.0001**	0.221
Mean Leaf Water Potential (MPa)																									**0**	0.250
Cluster weight (kg)																										**0**

Table A13 *p*-value correlation matrix for Cave Spring Cabernet franc 2015

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	March Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.000**	**0.002**	**0.000**	0.775	0.711	0.432	0.490	0.684	0.245	0.479	0.115	0.312	**0.010**	0.558	0.194	0.395	0.483	0.837	0.070	**0.022**	**0.025**	0.405	0.347	0.817	0.396	0.929
NDVI August		**0**	**< 0.0001**	**< 0.0001**	0.852	0.157	0.345	0.447	0.507	0.784	0.461	0.942	0.130	**0.004**	0.254	0.650	0.589	0.379	**0.001**	0.473	0.783	0.141	0.740	**0.016**	**0.019**	**0.028**	**0.039**
NDVI September			**0**	**< 0.0001**	0.141	0.357	0.558	0.296	0.784	0.681	0.763	0.888	0.538	**0.034**	0.275	0.894	0.959	0.367	0.696	0.410	0.169	0.165	0.092	0.683	**0.039**	0.051	**0.003**
Mean NDVI				**0**	0.390	0.347	0.653	0.954	0.767	0.503	0.803	0.607	0.521	**0.002**	0.419	0.917	0.999	0.556	0.088	0.534	0.223	**0.046**	0.370	0.126	**0.038**	**0.031**	**0.020**
Cluster number					**0**	**< 0.0001**	0.817	0.664	0.837	0.589	**0.037**	**0.023**	0.123	0.256	0.699	0.411	0.531	0.669	0.257	0.248	0.381	0.487	0.786	0.134	0.085	0.135	**< 0.0001**
Yield (kg/vine)						**0**	0.415	0.553	0.536	0.300	0.171	0.275	0.720	0.249	0.857	0.935	0.775	0.988	0.097	0.432	0.795	0.428	0.804	0.148	**0.043**	0.099	0.062
Berry weight (g)							**0**	0.221	0.706	0.145	**0.015**	0.053	0.758	0.097	0.163	0.067	0.791	0.055	0.058	0.869	0.100	0.942	0.174	0.671	0.921	0.524	0.733
Soluble Solids (°Brix)								**0**	**0.004**	0.609	**< 0.0001**	**0.001**	0.067	0.103	0.511	0.891	0.590	0.721	0.591	0.766	0.269	0.647	0.718	0.479	0.529	0.862	0.074
pH									**0**	**0.006**	0.942	**0.019**	0.784	0.497	0.054	0.247	0.723	**0.014**	0.261	0.811	0.500	0.339	0.386	0.896	0.892	0.732	0.326
Titratable Acidity (g/L)										**0**	0.484	0.336	0.535	0.134	**0.006**	0.645	0.592	0.053	0.677	0.405	0.222	0.904	0.425	0.886	0.214	0.296	0.149
Anthocyanins (mg/L)											**0**	**< 0.0001**	**< 0.0001**	0.697	0.308	0.817	0.366	0.761	0.165	0.738	0.260	0.770	0.907	0.551	0.086	0.213	0.096
Colour (au)												**0**	**< 0.0001**	0.226	0.543	0.798	0.125	0.810	0.119	0.851	0.187	0.953	0.677	0.733	0.263	0.357	**0.027**
Phenols (mg/L)													**0**	0.202	0.321	0.415	**0.010**	0.796	**0.000**	0.959	0.177	0.171	0.139	0.532	0.805	0.886	0.052
Vine size (kg)														**0**	0.871	0.177	**0.015**	0.702	0.524	0.790	**0.028**	0.430	0.169	0.204	0.591	0.442	0.617
January Bud LT_{50}															**0**	0.177	0.367	**0.001**	0.121	0.221	0.592	0.972	0.154	**0.016**	0.738	0.122	0.370
February Bud LT_{50}																**0**	0.228	**0.036**	0.511	0.668	0.782	0.664	0.172	0.894	0.933	0.710	0.245
March Bud LT_{50}																	**0**	0.932	0.113	0.311	0.092	0.703	**0.004**	0.555	0.982	0.345	0.247
Mean Bud LT_{50}																		**0**	0.395	0.753	0.924	0.694	0.462	0.169	0.767	0.340	0.443
Soil Moisture July (%)																			**0**	0.893	0.454	**< 0.0001**	**0.048**	0.288	0.097	0.525	0.369
Soil Moisture August (%)																				**0**	**0.000**	**< 0.0001**	**0.000**	0.670	0.854	0.158	0.595
Soil Moisture September (%)																					**0**	**< 0.0001**	**0.001**	0.701	0.425	0.134	0.355
Mean Soil Moisture (%)																						**0**	**0.023**	0.564	0.172	0.063	0.835
Leaf Water Potential July (MPa)																							**0**	**0.032**	0.096	**< 0.0001**	0.623
Leaf Water Potential August (MPa)																								**0**	**0.000**	**< 0.0001**	0.693
Leaf Water Potential September (MPa)																									**0**	**< 0.0001**	0.850
Mean Leaf Water Potential (MPa)																										**0**	0.645
Cluster weight (kg)																											**0**

Table A14 *p*-value correlation matrix for Coyote's Run Pinot noir East-West block 2014

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Cluster weight (kg)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (Mpa)	Leaf Water Potential August (Mpa)	Leaf Water Potential September (Mpa)	Mean Leaf Water Potential (Mpa)
NDVI July	**0**	**0.000**	**0.000**	**0.000**	0.952	0.587	0.379	0.248	0.837	**0.000**	0.535	0.169	0.537	0.091	0.988	**0.045**	0.650	0.060	0.087	0.750	0.089	0.173	0.496	0.692	0.827	0.530
NDVI August		**0**	**< 0.0001**	**< 0.0001**	0.976	0.801	0.503	0.871	**0.040**	**0.004**	0.897	**0.028**	0.167	0.763	0.610	0.193	0.564	0.437	0.229	0.336	**0.020**	0.089	**0.021**	0.111	0.495	0.606
NDVI September			**0**	**< 0.0001**	0.533	0.806	0.220	0.449	0.203	0.219	0.974	**0.041**	0.311	0.548	0.605	0.294	0.740	0.487	0.265	0.703	0.306	0.350	**0.049**	0.327	0.771	0.961
Mean NDVI				**0**	0.793	0.856	0.268	0.433	0.141	**0.004**	0.866	**0.023**	0.421	0.667	0.659	0.094	0.818	0.209	0.118	0.502	**0.047**	0.116	**0.041**	0.342	0.629	0.986
Cluster number					**0**	**< 0.0001**	**< 0.0001**	**0.000**	**0.000**	0.210	0.225	0.152	0.834	**0.020**	**0.010**	0.618	0.415	0.998	0.345	0.513	0.182	0.266	0.081	0.851	0.106	0.985
Yield (kg/vine)						**0**	**< 0.0001**	**0.000**	**0.003**	0.120	0.308	0.255	0.912	0.051	**0.012**	0.783	0.349	0.805	0.881	0.441	0.358	0.464	0.111	0.903	0.100	0.958
Cluster weight (kg)							**0**	**0.044**	0.174	0.896	0.161	0.855	0.807	0.855	0.258	0.770	0.843	0.888	0.266	0.095	0.981	0.734	0.550	0.700	0.546	0.748
Berry weight (g)								**0**	0.527	0.954	0.918	**0.004**	0.083	0.624	**0.014**	0.267	0.403	0.626	**0.029**	**0.004**	**0.006**	**0.002**	0.276	**0.039**	0.990	**0.012**
Soluble Solids (°Brix)									**0**	0.188	**0.006**	0.991	0.511	0.137	0.614	0.463	0.214	0.216	0.555	0.798	0.541	0.895	0.986	0.939	0.555	0.720
pH										**0**	**0.000**	**0.001**	0.745	0.583	0.198	0.596	0.694	0.524	0.197	0.090	**0.007**	**0.029**	0.855	0.236	0.999	0.330
Titratable Acidity (g/L)											**0**	0.409	0.179	0.855	0.304	0.417	0.602	0.687	0.507	0.944	0.769	0.758	0.981	0.257	0.333	0.131
Anthocyanins (mg/L)												**0**	**< 0.0001**	0.180	0.068	0.926	0.262	0.623	**0.028**	**0.001**	**0.001**	**0.000**	0.391	**0.002**	0.747	**0.002**
Colour (au)													**0**	**0.001**	0.144	0.566	0.212	0.874	0.103	**0.002**	**0.006**	**0.003**	0.128	0.508	0.300	**0.047**
Phenols (mg/L)														**0**	0.085	0.696	0.155	0.297	0.754	0.481	0.941	0.861	0.476	0.253	0.506	0.329
Vine size (kg)															**0**	0.848	0.230	0.654	0.178	**0.047**	0.143	0.058	0.531	0.493	0.705	0.243
January Bud LT_{50}																**0**	0.498	**< 0.0001**	0.103	0.238	0.064	0.075	**0.030**	0.185	0.314	0.610
February Bud LT_{50}																	**0**	**< 0.0001**	0.784	0.097	0.645	0.420	**0.001**	**< 0.0001**	**0.000**	0.452
Mean Bud LT_{50}																		**0**	0.230	0.068	0.078	0.060	0.859	0.206	**0.010**	0.969
Soil Moisture July (%)																			**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.771	0.248	0.529	0.124
Soil Moisture August (%)																				**0**	**< 0.0001**	**< 0.0001**	0.142	**0.000**	0.951	**0.015**
Soil Moisture September (%)																					**0**	**< 0.0001**	0.955	**0.028**	0.750	0.072
Mean Soil Moisture (%)																						**0**	0.570	**0.005**	0.897	**0.022**
Leaf Water Potential July (MPa)																							**0**	**0.000**	0.167	**0.011**
Leaf Water Potential August (MPa)																								**0**	0.442	**< 0.0001**
Leaf Water Potential September (MPa)																									**0**	**< 0.0001**
Mean Leaf Water Potential (MPa)																										**0**

Table A15 *p*-value correlation matrix for Coyote's Run Pinot noir East-West block 2015

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	March Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.001**	**0.000**	**0.000**	0.162	0.159	0.862	0.361	0.555	0.295	0.885	0.785	0.383	0.740	0.181	0.557	0.284	0.336	0.503	0.419	0.253	0.583	**0.004**	0.132	0.451	0.226	0.875
NDVI August		**0**	**0.019**	**< 0.0001**	0.285	0.885	0.087	0.689	0.634	0.326	0.527	0.458	0.697	0.174	0.330	0.443	0.093	0.067	0.308	0.114	0.204	0.459	**0.010**	0.059	0.570	0.051	0.467
NDVI September			**0**	**< 0.0001**	0.117	0.114	0.526	0.848	**0.021**	0.162	**0.024**	0.708	0.291	0.798	0.655	0.866	0.389	0.993	0.887	0.678	0.856	0.862	**0.016**	**0.004**	0.265	**0.011**	0.810
Mean NDVI				**0**	0.785	0.384	0.243	0.936	0.272	0.161	0.381	0.497	0.717	0.507	0.293	0.959	0.154	0.223	0.334	0.148	0.182	0.456	**0.000**	**0.011**	0.755	**0.018**	0.649
Cluster number					**0**	**< 0.0001**	0.665	0.071	0.893	0.310	**0.004**	**0.025**	**0.025**	0.970	0.773	0.894	0.988	0.754	0.248	0.857	0.647	0.871	0.353	0.762	0.448	0.376	0.373
Yield (kg/vine)						**0**	**0.047**	0.740	0.643	0.134	**0.000**	**0.001**	**0.004**	0.949	0.595	0.579	0.568	0.333	0.125	0.966	0.265	0.934	0.123	0.508	0.152	0.106	**0.019**
Berry weight (g)							**0**	**< 0.0001**	**< 0.0001**	**0.001**	**0.003**	**0.025**	**0.022**	0.303	0.129	0.324	0.206	**0.018**	0.372	0.266	0.266	0.829	**0.019**	0.139	**0.017**	**0.006**	**0.008**
Soluble Solids (°Brix)								**0**	**< 0.0001**	**< 0.0001**	**0.039**	0.716	**< 0.0001**	**0.041**	0.661	0.291	0.217	0.151	0.157	0.120	0.361	0.135	0.257	0.760	**0.002**	**0.025**	**0.032**
pH									**0**	**< 0.0001**	0.603	**0.002**	0.064	0.967	0.908	0.592	0.396	0.610	0.053	**0.010**	0.151	**0.022**	**0.047**	**0.035**	0.493	0.063	0.289
Titratable Acidity (g/L)										**0**	**0.028**	0.326	0.113	0.994	0.382	0.186	0.722	0.948	0.539	0.084	0.052	0.085	0.478	0.181	0.922	0.437	0.166
Anthocyanins (mg/L)											**0**	**< 0.0001**	**< 0.0001**	0.838	0.934	0.269	0.229	0.310	0.378	0.394	0.576	0.375	0.057	0.876	**0.003**	**0.014**	0.105
Colour (au)												**0**	0.289	0.793	0.413	0.865	0.617	0.497	0.184	0.327	0.390	0.216	0.689	0.919	**0.047**	0.203	0.088
Phenols (mg/L)													**0**	0.209	0.878	0.214	0.116	0.157	0.621	0.401	0.082	0.204	**0.025**	0.965	**< 0.0001**	**0.002**	0.068
Vine size (kg)														**0**	0.985	0.678	0.975	0.788	0.945	0.466	0.749	0.670	0.224	**0.031**	0.390	0.095	0.638
January Bud LT_{50}															**0**	0.186	0.832	**0.014**	0.133	**0.034**	0.359	0.075	0.589	0.935	0.827	0.759	0.464
February Bud LT_{50}																**0**	0.073	**0.029**	**0.012**	0.616	0.192	0.806	0.140	0.151	0.289	0.096	**0.044**
March Bud LT_{50}																	**0**	**0.006**	0.486	0.504	0.976	0.988	0.745	0.986	0.399	0.735	0.108
Mean Bud LT_{50}																		**0**	0.574	0.141	0.101	0.230	0.671	0.313	0.441	0.354	**0.011**
Soil Moisture July (%)																			**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.421	0.161	0.985	0.441	0.870
Soil Moisture August (%)																				**0**	**< 0.0001**	**< 0.0001**	0.850	0.502	0.542	0.630	0.684
Soil Moisture September (%)																					**0**	**< 0.0001**	**0.013**	0.720	0.809	0.326	0.120
Mean Soil Moisture (%)																						**0**	0.378	0.355	0.925	0.991	0.532
Leaf Water Potential July (MPa)																							**0**	**0.000**	**< 0.0001**	**< 0.0001**	0.621
Leaf Water Potential August (MPa)																								**0**	**0.001**	**< 0.0001**	0.877
Leaf Water Potential September (MPa)																									**0**	**< 0.0001**	0.223
Mean Leaf Water Potential (MPa)																										**0**	0.361
Cluster weight (kg)																											**0**

Table A16 *p*-value correlation table for Coyote's Run Pinot noir North-South block 2014

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.000**	**0.000**	**0.000**	0.082	0.062	0.793	0.928	0.230	0.074	0.424	0.907	0.462	0.162	**0.013**	0.058	0.332	0.124	0.790	0.357	0.213	0.507	0.144	0.339	0.086	0.219
NDVI August		**0**	**< 0.0001**	**< 0.0001**	0.060	0.068	0.972	0.408	0.263	**0.027**	0.146	0.573	0.627	0.754	**< 0.0001**	**0.000**	0.204	0.292	0.077	0.154	0.430	**0.046**	0.938	**0.000**	0.631	0.635
NDVI September			**0**	**< 0.0001**	**0.031**	**0.028**	0.316	0.521	**0.042**	**0.007**	0.644	0.766	0.422	0.829	**< 0.0001**	**0.006**	**0.019**	**0.016**	**0.046**	0.483	0.952	0.163	0.905	**0.002**	0.514	0.744
Mean NDVI				**0**	**0.022**	**0.019**	0.819	0.624	0.088	0.354	0.286	0.881	0.901	0.494	**< 0.0001**	**0.001**	0.078	**0.049**	0.218	0.733	0.754	0.124	0.545	0.058	0.701	0.605
Cluster number					**0**	**< 0.0001**	0.627	0.252	**0.011**	0.459	0.246	0.393	0.988	0.507	**0.001**	0.544	**0.033**	0.265	0.283	0.835	0.361	0.658	0.490	0.176	0.608	0.248
Yield (kg/vine)						**0**	0.613	0.296	**0.016**	0.431	0.118	0.315	0.734	0.518	**0.001**	0.577	**0.027**	0.276	0.206	0.847	0.324	0.697	0.382	0.171	0.703	**0.005**
Berry weight (g)							**0**	0.056	**< 0.0001**	**0.000**	0.068	**0.034**	0.486	**0.003**	0.902	0.660	0.916	0.170	0.818	0.100	0.149	0.110	0.156	0.765	0.051	0.475
Soluble Solids (°Brix)								**0**	**< 0.0001**	0.314	0.181	0.838	**< 0.0001**	0.416	0.830	0.549	0.914	0.615	0.511	0.808	0.902	0.888	0.121	0.866	0.287	0.507
pH									**0**	0.238	0.127	**0.000**	0.070	0.688	0.956	0.103	0.443	0.935	0.076	0.858	0.396	0.226	0.289	0.623	0.907	0.787
Titratable Acidity (g/L)										**0**	0.752	0.302	**0.047**	**0.030**	0.893	0.207	0.506	0.570	**0.016**	0.580	0.348	0.943	**0.000**	0.127	**0.004**	0.178
Anthocyanins (mg/L)											**0**	**< 0.0001**	0.266	0.818	**0.027**	**0.007**	**0.004**	**0.003**	**0.042**	**0.006**	**0.001**	**0.008**	0.684	0.093	**0.007**	0.081
Colour (au)												**0**	0.518	0.871	0.140	**0.046**	**0.045**	0.205	0.534	0.076	0.108	0.474	0.184	0.117	**0.049**	0.753
Phenols (mg/L)													**0**	0.315	0.931	0.979	0.958	0.869	0.123	0.194	0.277	0.136	**0.010**	0.305	0.935	0.709
Vine size (kg)														**0**	0.568	0.153	0.287	0.770	0.658	0.881	0.697	0.645	0.174	0.307	0.118	0.994
January Bud LT_{50}															**0**	**0.000**	**< 0.0001**	**0.002**	0.611	0.243	0.215	**0.001**	0.497	**< 0.0001**	**< 0.0001**	0.188
February Bud LT_{50}																**0**	**< 0.0001**	0.258	0.590	0.744	0.516	**0.001**	0.285	0.835	**0.014**	0.252
Mean Bud LT_{50}																	**0**	**0.005**	0.535	0.309	0.224	**< 0.0001**	0.978	**0.000**	**< 0.0001**	0.134
Soil Moisture July (%)																		**0**	**0.001**	**0.000**	**< 0.0001**	**0.012**	0.128	0.411	0.311	0.376
Soil Moisture August (%)																			**0**	**0.000**	**< 0.0001**	**0.027**	**0.021**	0.783	0.898	0.060
Soil Moisture September (%)																				**0**	**< 0.0001**	0.462	0.864	**0.045**	0.548	0.871
Mean Soil Moisture (%)																					**0**	**0.014**	0.074	0.608	0.840	0.199
Leaf Water Potential July (MPa)																						**0**	0.189	0.124	**< 0.0001**	0.755
Leaf Water Potential August (MPa)																							**0**	0.270	**< 0.0001**	0.507
Leaf Water Potential September (MPa)																								**0**	**< 0.0001**	0.687
Mean Leaf Water Potential (MPa)																									**0**	0.442
Cluster weight (kg)																										**0**

Table A17 *p*-value correlation table for Coyote's Run Pinot noir North-South block 2015

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Anthocya-nins (mg/L)	Colour (au)	Phenols (mg/L)	Vine size (kg)	January Bud LT$_{50}$	February Bud LT$_{50}$	March Bud LT$_{50}$	Mean Bud LT$_{50}$	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.000**	**0.002**	**0.000**	0.085	0.188	0.283	0.109	0.560	0.536	**0.020**	**0.009**	**0.023**	0.422	**0.030**	0.494	0.361	**0.045**	**0.001**	**0.017**	0.126	**0.002**	**0.025**	0.139	**0.021**	**0.037**	0.862
NDVI August		**0**	**< 0.0001**	**< 0.0001**	**0.016**	0.088	0.097	0.952	0.514	0.766	0.961	0.970	**0.004**	**0.040**	0.511	0.981	0.653	0.743	0.108	0.061	0.641	0.093	0.736	0.189	0.907	0.312	0.369
NDVI September			**0**	**< 0.0001**	0.078	0.091	0.341	0.768	0.914	0.416	0.752	0.601	0.064	**0.031**	0.731	0.781	0.232	0.223	0.059	0.837	0.510	0.493	0.607	0.092	0.758	0.274	0.287
Mean NDVI				**0**	**0.013**	0.051	0.122	0.471	0.599	0.869	0.176	0.232	0.587	**0.049**	0.145	0.764	0.520	0.130	**0.002**	**0.039**	0.446	**0.011**	0.220	0.060	0.172	0.060	0.940
Cluster number					**0**	**< 0.0001**	**0.006**	0.117	**0.001**	0.109	0.659	0.272	0.405	**0.006**	0.919	**0.003**	0.124	0.439	**0.011**	**0.001**	0.087	**0.001**	0.580	0.334	0.880	0.800	0.982
Yield (kg/vine)						**0**	**0.004**	0.318	**0.001**	0.224	0.536	0.244	0.655	**0.047**	0.903	**0.001**	0.171	0.339	**0.019**	**0.004**	0.134	**0.004**	0.721	0.326	0.918	0.709	0.496
Berry weight (g)							**0**	**0.033**	**0.000**	**0.012**	0.449	0.166	0.262	0.650	0.482	0.919	0.070	0.070	0.897	0.115	0.735	0.413	0.112	0.610	0.209	**0.049**	0.645
Soluble Solids (°Brix)								**0**	0.294	**< 0.0001**	0.792	**0.035**	0.057	0.547	0.708	0.536	0.197	0.533	0.664	0.340	0.812	0.629	0.224	0.880	**0.025**	**0.014**	0.204
pH									**0**	0.554	**0.013**	**< 0.0001**	0.763	0.620	0.624	**0.004**	0.345	0.087	**0.042**	**0.009**	0.062	**0.006**	0.206	0.647	**0.004**	**0.021**	0.235
Titratable Acidity (g/L)										**0**	0.131	0.482	0.357	0.996	0.447	0.189	0.075	0.453	**0.002**	0.378	0.220	**0.022**	0.388	0.914	0.142	0.306	0.825
Anthocyanins (mg/L)											**0**	**< 0.0001**	**0.032**	0.759	0.567	0.291	0.495	0.376	0.419	0.316	0.447	0.278	0.348	0.519	**0.003**	0.066	0.243
Colour (au)												**0**	**< 0.0001**	0.156	1.000	**0.023**	0.158	0.511	0.278	0.563	0.638	0.640	0.634	0.443	**< 0.0001**	**0.002**	0.309
Phenols (mg/L)													**0**	0.747	0.481	0.567	**0.010**	0.111	0.110	0.902	0.915	0.516	0.555	**0.003**	0.076	0.993	0.996
Vine size (kg)														**0**	0.250	0.878	0.396	0.657	**0.026**	0.654	0.294	0.101	0.976	0.423	0.622	0.369	0.587
January Bud LT$_{50}$															**0**	0.362	0.793	**0.004**	0.446	0.185	0.573	0.735	0.087	0.367	0.170	0.323	0.648
February Bud LT$_{50}$																**0**	0.109	0.610	0.174	0.105	0.111	**0.041**	**0.032**	0.652	0.076	0.216	0.487
March Bud LT$_{50}$																	**0**	0.333	0.381	0.581	**0.024**	0.132	0.448	0.978	0.195	0.388	0.953
Mean Bud LT$_{50}$																		**0**	0.246	0.682	0.550	0.859	0.587	0.628	0.071	0.192	0.336
Soil Moisture July (%)																			**0**	**< 0.0001**	**0.001**	**< 0.0001**	0.410	0.767	0.969	0.883	0.316
Soil Moisture August (%)																				**0**	**< 0.0001**	**< 0.0001**	0.163	**0.006**	0.152	0.916	0.650
Soil Moisture September (%)																					**0**	**< 0.0001**	**0.027**	0.241	0.051	0.080	0.373
Mean Soil Moisture (%)																						**0**	0.293	0.159	0.182	0.498	0.942
Leaf Water Potential July (MPa)																							**0**	**< 0.0001**	0.951	0.591	0.995
Leaf Water Potential August (MPa)																								**0**	0.831	**< 0.0001**	0.110
Leaf Water Potential September (MPa)																									**0**	**< 0.0001**	0.222
Mean Leaf Water Potential (MPa)																										**0**	**0.043**
Cluster weight (kg)																											**0**

Table A18 *p*-value correlation table for Cave Spring Riesling in 2014

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Free Volatile Terpenes (mg/L)	Potentially Volatile Terpenes (mg/L)	Vine size (kg)	January Bud LT$_{50}$	February Bud LT$_{50}$	Mean Bud LT$_{50}$	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.018**	**0.001**	**0.000**	**0.038**	**0.007**	0.276	0.136	0.143	0.575	0.128	0.189	**0.038**	**0.039**	0.424	0.216	0.408	0.932	0.968	0.560	0.217	0.362	**0.030**	0.060	0.082
NDVI August		**0**	**< 0.0001**	**< 0.0001**	**0.009**	0.439	0.206	0.059	0.567	0.617	**0.048**	0.680	0.175	0.590	0.194	0.231	0.233	0.884	0.892	0.386	0.666	0.116	0.182	0.156	**0.004**
NDVI September			**0**	**< 0.0001**	0.172	0.724	0.326	0.645	**0.042**	0.583	0.052	0.069	0.847	0.257	**0.012**	**0.016**	0.424	0.831	0.944	0.598	0.788	0.917	0.339	0.662	**0.001**
Mean NDVI				**0**	0.193	0.558	0.766	0.333	0.336	0.714	**0.017**	0.236	0.900	0.767	**0.029**	0.135	0.232	0.937	0.993	0.405	0.997	0.628	0.585	0.884	0.000
Cluster number					**0**	**< 0.0001**	0.243	0.632	**0.000**	0.740	0.731	0.630	**< 0.0001**	**0.007**	0.609	0.058	0.056	**0.040**	**0.009**	**0.002**	0.464	0.792	0.345	0.409	0.935
Yield (kg/vine)						**0**	0.333	0.499	**0.009**	0.735	0.969	0.846	**< 0.0001**	**0.043**	0.183	0.371	0.195	**0.009**	**0.008**	**0.005**	0.844	0.669	0.418	0.713	**< 0.0001**
Berry weight (g)							**0**	0.491	**0.008**	0.113	0.530	**0.011**	0.306	0.982	0.287	0.528	0.375	0.138	0.183	0.739	0.116	0.060	**0.006**	**0.008**	0.893
Soluble Solids (°Brix)								**0**	**0.027**	0.559	0.061	0.272	0.415	0.681	0.125	0.591	0.137	0.161	0.642	0.082	0.494	0.118	0.501	0.270	0.736
pH									**0**	**0.001**	0.879	0.566	0.889	**0.044**	0.509	0.201	0.391	0.800	0.714	0.403	0.079	0.406	0.119	0.100	0.707
Titratable Acidity (g/L)										**0**	0.073	0.744	0.539	**0.001**	0.463	**0.022**	0.981	0.277	0.487	0.899	**0.008**	0.724	**0.042**	0.084	0.834
Free Volatile Terpenes (mg/L)											**0**	0.873	0.459	**0.037**	0.115	**0.008**	0.573	0.308	0.228	0.717	0.142	**0.004**	0.873	0.203	0.338
Potentially Volatile Terpenes (mg/L)												**0**	0.902	0.118	0.333	0.062	0.891	0.389	0.058	0.396	0.162	**0.002**	**< 0.0001**	**< 0.0001**	0.801
Vine size (kg)													**0**	**0.030**	0.865	0.091	0.948	0.474	0.299	0.512	0.734	0.936	0.381	0.573	0.886
January Bud LT$_{50}$														**0**	0.850	**< 0.0001**	0.301	**0.007**	**0.049**	0.392	**0.014**	**0.036**	0.520	0.663	0.276
February Bud LT$_{50}$															**0**	**< 0.0001**	0.439	0.466	0.677	0.336	0.741	**0.038**	0.874	0.376	0.050
Mean Bud LT$_{50}$																**0**	0.191	0.072	0.167	0.876	**0.025**	0.588	0.658	0.883	**0.041**
Soil Moisture July (%)																	**0**	0.979	0.260	**< 0.0001**	0.664	0.351	0.078	0.150	0.316
Soil Moisture August (%)																		**0**	**< 0.0001**	**< 0.0001**	0.553	0.190	0.619	0.373	0.101
Soil Moisture September (%)																			**0**	**< 0.0001**	0.777	0.084	0.277	0.197	0.475
Mean Soil Moisture (%)																				**0**	0.994	0.710	0.474	0.777	0.924
Leaf Water Potential July (MPa)																					**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.196
Leaf Water Potential August (MPa)																						**0**	**< 0.0001**	**< 0.0001**	0.187
Leaf Water Potential September (MPa)																							**0**	**< 0.0001**	0.838
Mean Leaf Water Potential (MPa)																								**0**	0.361
Cluster weight (kg)																									**0**

Table A19 *p*-value correlation table for Cave Spring Riesling in 2015

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Free Volatile Terpenes (mg/L)	Potentially Volatile Terpenes (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	March Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.000**	**0.002**	**0.000**	0.577	0.664	0.592	0.684	0.418	0.768	**0.006**	0.719	0.239	0.980	0.307	0.260	0.516	0.638	0.273	0.400	0.910	0.901	0.141	**0.039**	0.104	0.956
NDVI August		**0**	**< 0.0001**	**< 0.0001**	0.150	**0.015**	0.908	0.656	0.316	0.138	0.094	0.912	0.197	0.975	0.880	0.703	0.889	0.174	0.597	**0.045**	0.974	0.757	0.637	0.260	0.686	0.217
NDVI September			**0**	**< 0.0001**	0.412	0.740	0.491	0.631	0.196	0.688	0.154	0.669	**0.017**	0.744	0.076	0.366	0.579	0.574	0.787	0.783	0.788	0.366	0.839	0.364	0.455	0.676
Mean NDVI				**0**	0.600	0.280	0.653	0.578	0.799	0.355	**0.014**	0.784	**0.044**	0.881	0.259	0.355	0.604	0.871	0.563	0.271	0.888	0.860	0.368	0.466	0.424	0.469
Cluster number					**0**	**< 0.0001**	0.353	0.136	**0.006**	**0.004**	0.935	0.791	0.858	0.061	0.834	0.635	0.154	0.567	0.104	0.550	0.217	0.806	0.908	0.957	0.891	0.122
Yield (kg/vine)						**0**	0.424	0.077	**0.005**	**0.029**	0.608	0.941	**0.032**	0.478	0.565	0.093	0.196	0.912	0.566	0.700	0.719	0.245	0.279	0.189	0.160	**< 0.0001**
Berry weight (g)							**0**	**0.013**	**0.000**	0.182	0.226	0.119	0.314	0.486	0.933	0.959	0.597	0.823	0.733	0.173	0.746	0.621	0.511	0.785	0.778	0.743
Soluble Solids (°Brix)								**0**	**0.007**	0.102	0.381	0.890	0.902	0.926	0.386	0.263	0.892	0.283	0.567	0.132	0.363	0.412	0.433	0.482	0.373	0.414
pH									**0**	**0.001**	0.071	0.542	0.079	0.516	0.983	0.686	0.689	0.741	0.511	0.070	0.371	0.564	0.390	**0.022**	0.105	0.303
Titratable Acidity (g/L)										**0**	0.107	0.720	0.194	0.381	0.812	0.583	0.532	0.132	0.633	**0.048**	0.749	0.189	0.129	0.095	0.070	0.837
Free Volatile Terpenes (mg/L)											**0**	0.322	0.780	0.104	0.432	0.292	**0.048**	0.357	0.199	0.369	0.784	**0.006**	0.789	0.060	0.706	0.531
Potentially Volatile Terpenes (mg/L)												**0**	0.428	0.628	0.508	0.799	0.793	0.386	0.189	**0.041**	0.062	0.657	**< 0.0001**	0.933	**0.049**	0.695
Vine size (kg)													**0**	0.444	0.859	0.853	0.530	0.943	0.471	0.107	0.684	0.541	0.974	0.305	0.512	**0.008**
January Bud LT_{50}														**0**	0.890	0.666	**< 0.0001**	0.641	0.204	0.683	0.662	0.267	0.918	0.776	0.962	0.494
February Bud LT_{50}															**0**	0.365	0.087	0.427	0.938	0.959	0.676	**0.030**	0.422	0.208	0.157	0.676
March Bud LT_{50}																**0**	0.053	0.899	0.882	0.249	0.627	0.172	0.568	0.113	0.192	**0.003**
Mean Bud LT_{50}																	**0**	0.930	0.291	0.996	0.709	0.868	0.603	0.262	0.422	0.717
Soil Moisture July (%)																		**0**	**< 0.0001**	0.055	**< 0.0001**	0.740	0.678	0.260	0.783	0.652
Soil Moisture August (%)																			**0**	**0.010**	**< 0.0001**	0.813	0.125	0.315	0.218	0.619
Soil Moisture September (%)																				**0**	**< 0.0001**	0.386	0.299	0.135	0.161	0.848
Mean Soil Moisture (%)																					**0**	0.527	0.191	0.597	0.319	0.726
Leaf Water Potential July (MPa)																						**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.125
Leaf Water Potential August (MPa)																							**0**	**< 0.0001**	**< 0.0001**	0.122
Leaf Water Potential September (MPa)																								**0**	**< 0.0001**	0.071
Mean Leaf Water Potential (MPa)																									**0**	0.052
Cluster weight (kg)																										**0**

Table A20 *p*-value correlation table for Lambert Riesling in 2014

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Free Volatile Terpenes (mg/L)	Potentially Volatile Terpenes (mg/L)	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	**0.000**	**0.000**	**0.000**	0.354	0.398	0.631	**0.033**	0.157	0.602	**0.024**	**0.000**	0.594	0.788	0.769	0.771	**0.012**	0.503	0.072	**0.038**	0.826
NDVI August		**0**	**< 0.0001**	**< 0.0001**	**0.008**	**0.002**	0.092	**0.011**	0.052	0.902	**0.001**	**< 0.0001**	0.127	0.722	0.611	0.426	**0.001**	0.385	0.310	**0.006**	0.655
NDVI September			**0**	**< 0.0001**	**0.025**	**0.005**	0.122	0.082	**0.049**	0.461	**0.003**	**< 0.0001**	0.075	0.722	0.207	0.772	**0.003**	0.841	0.709	0.074	0.981
Mean NDVI				**0**	**0.024**	**0.009**	0.147	**0.021**	**0.047**	0.818	**0.002**	**< 0.0001**	0.222	0.956	0.411	0.719	**0.001**	0.802	0.304	**0.016**	0.808
Cluster number					**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0.002**	0.761	0.972	0.139	0.834	**0.020**	0.820	0.249	0.465	0.608	0.545	**< 0.0001**
Yield (kg/vine)						**0**	**0.024**	**< 0.0001**	**< 0.0001**	0.142	0.661	0.408	0.617	0.785	0.339	0.993	**0.015**	0.195	0.364	0.211	0.533
Berry weight (g)							**0**	**0.002**	**0.002**	0.107	0.593	0.496	**0.001**	0.419	**0.008**	0.738	0.323	0.613	0.606	0.285	**< 0.0001**
Soluble Solids (°Brix)								**0**	**< 0.0001**	**< 0.0001**	**0.049**	0.067	0.968	0.648	0.430	0.604	**0.001**	0.377	0.111	**0.002**	**0.027**
pH									**0**	**0.000**	**0.031**	**0.048**	0.614	0.071	0.150	0.084	0.089	0.722	0.271	0.084	0.056
Titratable Acidity (g/L)										**0**	0.543	0.566	0.223	0.657	0.919	0.673	**0.040**	0.148	0.070	**0.003**	**0.023**
Free Volatile Terpenes (mg/L)											**0**	**< 0.0001**	0.095	0.902	0.557	0.222	0.147	0.059	**0.006**	0.124	0.683
Potentially Volatile Terpenes (mg/L)												**0**	0.748	0.664	0.296	0.416	0.459	0.413	**0.001**	**0.004**	0.669
Soil Moisture July (%)													**0**	0.066	0.349	**< 0.0001**	0.566	0.907	**0.003**	**0.037**	**0.028**
Soil Moisture August (%)														**0**	**< 0.0001**	**< 0.0001**	0.294	0.155	0.700	0.334	0.942
Soil Moisture September (%)															**0**	**< 0.0001**	0.217	0.241	0.341	0.072	0.065
Mean Soil Moisture (%)																**0**	0.495	0.224	0.163	0.961	0.685
Leaf Water Potential July (MPa)																	**0**	**0.006**	0.445	**< 0.0001**	0.125
Leaf Water Potential August (MPa)																		**0**	0.814	**< 0.0001**	0.561
Leaf Water Potential September (MPa)																			**0**	**< 0.0001**	0.692
Mean Leaf Water Potential (MPa)																				**0**	0.425
Cluster weight (kg)																					**0**

Table A21 *p*-value correlation table for Lambert Riesling in 2015

Table includes all NDVI measurements, berry composition and vine characteristics. The significance level is α=0.05, and bolded values are significant.

Variables	NDVI July	NDVI August	NDVI September	Mean NDVI	Cluster number	Yield (kg/vine)	Berry weight (g)	Soluble Solids (°Brix)	pH	Titratable Acidity (g/L)	Free Volatile Terpenes (mg/L)	Potentially Volatile Terpenes (mg/L)	Vine size (kg)	January Bud LT_{50}	February Bud LT_{50}	March Bud LT_{50}	Mean Bud LT_{50}	Soil Moisture July (%)	Soil Moisture August (%)	Soil Moisture September (%)	Mean Soil Moisture (%)	Leaf Water Potential July (MPa)	Leaf Water Potential August (MPa)	Leaf Water Potential September (MPa)	Mean Leaf Water Potential (MPa)	Cluster weight (kg)
NDVI July	**0**	0.157	**0.006**	**0.003**	0.996	0.763	0.367	0.051	0.716	**0.002**	**0.000**	**0.000**	0.826	0.730	**0.050**	0.195	0.232	**0.000**	**0.000**	**0.000**	**0.000**	**0.012**	0.108	0.076	0.868	0.911
NDVI August		**0**	**0.021**	**0.003**	0.556	0.226	0.574	0.791	0.848	0.340	0.771	0.718	0.682	0.116	0.438	0.670	0.440	0.386	0.958	0.441	0.979	0.845	0.421	**0.020**	0.052	0.231
NDVI September			**0**	**< 0.0001**	0.386	0.756	**0.040**	0.060	0.486	0.703	0.965	**0.011**	0.185	**0.034**	0.512	0.778	0.298	0.599	0.385	0.424	0.811	0.089	**0.001**	**0.002**	0.860	0.056
Mean NDVI				**0**	0.388	0.910	0.151	0.555	0.649	0.116	**0.016**	0.295	0.242	**0.004**	0.876	0.328	0.076	**0.007**	**0.000**	**0.028**	**0.001**	0.944	**0.030**	0.066	0.777	0.068
Cluster number					**0**	**< 0.0001**	**0.011**	0.334	**< 0.0001**	**0.033**	0.385	0.831	0.883	0.962	0.460	0.224	0.563	0.463	0.204	**0.007**	0.067	0.652	0.244	0.744	0.381	**< 0.0001**
Yield (kg/vine)						**0**	0.680	0.236	**0.000**	0.154	0.364	0.629	0.932	0.545	0.940	0.393	0.874	0.669	0.570	**0.027**	0.213	0.618	0.425	0.082	0.152	0.397
Berry weight (g)							**0**	0.276	**0.030**	**0.006**	0.951	0.400	0.460	0.435	0.745	0.597	0.451	0.310	**0.016**	0.608	0.126	0.107	0.320	0.086	0.764	**0.000**
Soluble Solids (°Brix)								**0**	**< 0.0001**	**0.031**	0.105	**0.016**	0.598	0.463	0.145	0.212	0.187	0.091	0.843	0.554	0.281	**0.021**	0.138	0.947	0.181	0.663
pH									**0**	**< 0.0001**	**0.020**	0.058	0.501	0.557	0.713	0.673	0.536	0.913	0.947	0.146	0.598	0.125	0.053	0.395	0.058	0.051
Titratable Acidity (g/L)										**0**	**< 0.0001**	**< 0.0001**	0.567	0.223	0.754	0.866	0.352	**0.002**	0.355	0.296	**0.031**	0.077	**0.008**	0.087	**0.004**	0.130
Free Volatile Terpenes (mg/L)											**0**	**< 0.0001**	0.589	0.673	0.508	0.442	0.483	**< 0.0001**	**0.004**	0.052	**0.000**	**0.004**	**0.017**	0.675	**0.032**	0.969
Potentially Volatile Terpenes (mg/L)												**0**	0.917	**0.013**	0.440	**0.002**	**0.006**	**< 0.0001**	**0.011**	**0.004**	**< 0.0001**	**< 0.0001**	**< 0.0001**	0.240	**0.009**	0.459
Vine size (kg)													**0**	0.399	**0.014**	0.116	0.073	0.735	0.768	0.956	0.809	0.427	0.847	0.261	0.277	0.643
January Bud LT_{50}														**0**	0.517	0.052	**0.001**	**0.007**	0.059	0.265	**0.024**	0.728	0.970	0.216	0.262	0.250
February Bud LT_{50}															**0**	0.307	0.077	0.250	0.423	0.261	0.218	0.408	0.749	0.386	0.282	0.422
March Bud LT_{50}																**0**	**0.008**	**0.008**	**0.035**	**0.040**	**0.003**	0.588	0.100	0.897	0.499	0.667
Mean Bud LT_{50}																	**0**	**0.002**	**0.036**	0.096	**0.004**	0.843	0.650	0.673	0.873	0.250
Soil Moisture July (%)																		**0**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0.017**	0.301	0.937	0.293	0.413
Soil Moisture August (%)																			**0**	**< 0.0001**	**< 0.0001**	0.186	0.437	0.367	0.525	**0.007**
Soil Moisture September (%)																				**0**	**< 0.0001**	0.185	0.814	0.252	0.588	0.063
Mean Soil Moisture (%)																					**0**	**0.036**	0.913	0.880	0.613	**0.039**
Leaf Water Potential July (MPa)																						**0**	**0.005**	0.419	**< 0.0001**	0.340
Leaf Water Potential August (MPa)																							**0**	0.096	**< 0.0001**	0.064
Leaf Water Potential September (MPa)																								**0**	**< 0.0001**	0.498
Mean Leaf Water Potential (MPa)																									**0**	0.538
Cluster weight (kg)																										**0**

Table A22 Spatial Autocorrelation (Moran's *I*) results for Lambert Cabernet franc 2014-2015: Moran's *I* Index values, z-scores and p-value. Patterns are expressed as clustered, dispersed, or random and are indicated for the corresponding attribute (✓), February bud (LT_{50}) was not collected in 2015.

LAMBERT CABERNET FRANC							
	Year	**Moran's Index**	**z-score**	**p-value**	**Dispersed**	**Random**	**Clustered**
NDVI July	**2014**	0.2264	1.9409	0.0523			✓
	2015	0.0962	0.9540	0.3401		✓	
NDVI August	**2014**	0.0841	0.7864	0.4316		✓	
	2015	0.5029	4.1496	0.0000			✓
NDVI September	**2014**	0.0854	0.7945	0.4269		✓	
	2015	0.4352	3.6091	0.0003			✓
Cluster number (per vine)	**2014**	-0.1237	-0.8913	0.3728		✓	
	2015	-0.0532	-0.3276	0.7432		✓	
Yield (kg/vine)	**2014**	-0.0816	-0.5530	0.5803		✓	
	2015	0.0142	0.2211	0.8250		✓	
Cluster weight (kg)	**2014**	0.1623	1.4338	0.1516		✓	
	2015	-0.0135	-0.0027	0.9978		✓	
Berry weight (g)	**2014**	0.0054	0.1493	0.8813		✓	
	2015	-0.0619	-0.3925	0.6947		✓	
Soluble Solids (°Brix)	**2014**	0.0221	0.2831	0.7771		✓	
	2015	-0.2385	-1.8812	0.0599	✓		
pH	**2014**	-0.1389	-1.0610	0.2887		✓	
	2015	0.0197	0.2649	0.7911		✓	
Titratable Acidity (g/L)	**2014**	0.1188	1.0710	0.2841		✓	
	2015	-0.0970	-0.6865	0.4924		✓	
Anthocyanins (mg/L)	**2014**	0.1516	1.3015	0.1931		✓	
	2015	-0.0022	0.0890	0.9291		✓	
Colour (au)	**2014**	0.1508	1.2916	0.1965		✓	
	2015	0.1228	-0.8880	0.3746		✓	
Phenols (mg/L)	**2014**	0.1130	0.9915	0.3214		✓	
	2015	-0.0880	-0.6080	0.5432		✓	
Vine size (kg)	**2014**	0.1048	0.9519	0.3411		✓	
	2015	0.0235	0.2970	0.7665		✓	
January Bud LT_{50}	**2014**	0.3467	2.8966	0.0038			✓
	2015	-0.0942	-0.0145	0.9885		✓	
February Bud LT_{50}	**2014**	-0.1545	-1.1354	0.2562		✓	
	2015	--	--	--			
Mean Bud LT_{50}	**2014**	0.0521	0.5293	0.5966		✓	
	2015	--	--	--			
Soil Moisture July (%)	**2014**	0.1064	0.9628	0.3357		✓	
	2015	0.2077	1.7999	0.0719			✓
Soil Moisture August (%)	**2014**	0.4081	3.3974	0.0007			✓
	2015	0.4439	3.7463	0.0002			✓
Soil Moisture September (%)	**2014**	0.4021	3.3586	0.0008			✓
	2015	0.4357	3.6505	0.0003			✓
Mean Soil Moisture (%)	**2014**	0.4225	3.5078	0.0005			✓
	2015	0.4883	4.0517	0.0001			✓
Leaf Water Potential July (Mpa)	**2014**	0.7712	6.3298	0.0000			✓
	2015	-0.5548	-2.1405	0.0323	✓		
Leaf Water Potential August (Mpa)	**2014**	0.5525	4.5911	0.0000			✓
	2015	-0.0125	0.1703	0.8647		✓	
Leaf Water Potential September (Mpa)	**2014**	-0.0801	-0.5402	0.5890		✓	
	2015	0.1341	0.7967	0.4256		✓	
Mean Leaf Water Potential (Mpa)	**2014**	0.7923	6.4628	0.0000			✓
	2015	0.0921	0.6166	0.5375		✓	

Table A23 Spatial Autocorrelation (Moran's *I*) results for Cave Spring Cabernet franc 2014-2015: Moran's *I* Index values, z-scores and p-value. Patterns are expressed as clustered, dispersed, or random and are indicated for the corresponding attribute (✓), February bud (LT_{50}) was not collected in 2015.

CAVE SPRING CABERNET FRANC							
	Year	**Moran's Index**	**z-score**	**p-value**	**Dispersed**	**Random**	**Clustered**
NDVI July	**2014**	0.4427	3.5653	0.0004			✓
	2015	0.1834	1.5496	0.1212		✓	
NDVI August	**2014**	0.5819	4.6505	0.0000			✓
	2015	0.3946	3.1979	0.0014			✓
NDVI September	**2014**	0.3890	3.1553	0.0016			✓
	2015	0.2690	2.2051	0.0274			✓
Cluster number (per	**2014**	0.0788	0.7449	0.4563		✓	
	2015	-0.3294	-2.4741	0.0134	✓		
Yield (kg/vine)	**2014**	0.0820	0.7586	0.4481		✓	
	2015	-0.0179	-0.0343	0.9726		✓	
Cluster weight (kg)	**2014**	-0.0072	0.0496	0.9604		✓	
	2015	-0.0557	-0.3302	0.7412		✓	
Berry weight (g)	**2014**	0.1296	1.1257	0.2603		✓	
	2015	0.0043	0.1428	0.8864		✓	
Soluble Solids (°Brix)	**2014**	0.1117	1.0054	0.3147		✓	
	2015	0.0082	0.1823	0.8554		✓	
pH	**2014**	0.0871	0.7894	0.4299		✓	
	2015	0.2256	1.8767	0.0606			✓
Titratable Acidity (g/L)	**2014**	-0.1210	-0.8645	0.3873		✓	
	2015	0.2093	1.7465	0.0807			✓
Anthocyanins (mg/L)	**2014**	0.1855	1.5757	0.1151		✓	
	2015	0.0099	0.1847	0.8535		✓	
Colour (au)	**2014**	0.2310	1.9344	0.0531			✓
	2015	-0.0444	-0.2418	0.8089		✓	
Phenols (mg/L)	**2014**	0.0907	0.8264	0.4086		✓	
	2015	0.1508	1.2853	0.1987		✓	
Vine size (kg)	**2014**	0.1999	1.6860	0.0918			✓
	2015	0.0046	0.1419	0.8871		✓	
January Bud LT_{50}	**2014**	0.3905	3.1426	0.0017			✓
	2015	0.0048	0.3668	0.7137		✓	
February Bud LT_{50}	**2014**	0.7519	5.9812	0.0000			✓
	2015	--	--	--			
Mean Bud LT_{50}	**2014**	0.6181	4.9230	0.0000			✓
	2015	--	--	--			
Soil Moisture July (%)	**2014**	0.2785	2.2940	0.0218			✓
	2015	0.1473	1.2562	0.2090		✓	
Soil Moisture August (%)	**2014**	0.1286	1.1131	0.2657		✓	
	2015	-0.3682	-2.8140	0.0049	✓		
Soil Moisture September (%)	**2014**	0.1498	1.2748	0.2024		✓	
	2015	0.0836	0.7585	0.4482		✓	
Mean Soil Moisture (%)	**2014**	0.3679	2.9816	0.0029			✓
	2015	0.2349	-1.7311	0.0834	✓		
Leaf Water Potential July (Mpa)	**2014**	0.2494	2.0521	0.0402			✓
	2015	-0.0347	0.1395	0.8891		✓	
Leaf Water Potential August (Mpa)	**2014**	-0.1453	-1.0288	0.3036		✓	
	2015	0.2049	1.0407	0.2980		✓	
Leaf Water Potential September (Mpa)	**2014**	0.1243	1.0716	0.2839		✓	
	2015	0.0113	0.3560	0.7218		✓	
Mean Leaf Water Potential (Mpa)	**2014**	0.1749	1.4657	0.1427		✓	
	2015	0.0348	0.4412	0.6591		✓	

Table A24 Spatial Autocorrelation (Moran's *I*) results for Coyote's Run (East-West) 2014-2015: Moran's *I* Index values, z-scores and p-value. Patterns are expressed as clustered, dispersed, or random and are indicated for the corresponding attribute (✓), February bud (LT_{50}) was not collected in 2015.

COYOTE'S RUN PINOT NOIR (E-W)							
	Year	**Moran's Index**	**z-score**	**p-value**	**Dispersed**	**Random**	**Clustered**
NDVI July	**2014**	0.0640	0.7214	0.4707		✓	
	2015	0.5235	6.2963	0.0000			✓
NDVI August	**2014**	0.6524	6.2484	0.0000			✓
	2015	0.1347	2.0801	0.0375			✓
NDVI September	**2014**	-0.1125	-0.9456	0.3444		✓	
	2015	-0.0024	0.1232	0.9019		✓	
Cluster number (per vine)	**2014**	-0.1459	-1.2687	0.2045		✓	
	2015	-0.0107	0.0123	0.9902		✓	
Yield (kg/vine)	**2014**	-0.1421	-1.2468	0.2125		✓	
	2015	0.0485	0.5743	0.5658		✓	
Cluster weight (kg)	**2014**	-0.2161	-1.9248	0.0543	✓		
	2015	0.0171	0.2793	0.7800		✓	
Berry weight (g)	**2014**	0.0697	0.7781	0.4365		✓	
	2015	-0.0223	-0.0994	0.9208		✓	
Soluble Solids (°Brix)	**2014**	-0.2257	-2.0155	0.0439	✓		
	2015	0.0171	0.2944	0.7684		✓	
pH	**2014**	0.1688	1.7072	0.0878			✓
	2015	0.0464	0.5860	0.5579		✓	
Titratable Acidity (g/L)	**2014**	0.0945	1.0120	0.3115		✓	
	2015	0.0031	0.1666	0.8677		✓	
Anthocyanins (mg/L)	**2014**	0.2584	2.5457	0.0109			✓
	2015	0.1236	1.3642	0.1725		✓	
Colour (au)	**2014**	-0.0074	0.0445	0.9645		✓	
	2015	0.0104	0.2285	0.8192		✓	
Phenols (mg/L)	**2014**	0.1137	1.1995	0.2303		✓	
	2015	0.3797	3.7237	0.0002			✓
Vine size (kg)	**2014**	-0.0274	-0.1453	0.8845		✓	
	2015	-0.1417	-1.2296	0.2189		✓	
January Bud LT_{50}	**2014**	-0.0676	-0.5266	0.5984		✓	
	2015	0.5342	2.0835	0.0372			✓
February Bud LT_{50}	**2014**	0.3113	3.0507	0.0023			✓
	2015	--	--	--			
Mean Bud LT_{50}	**2014**	-0.0426	-0.2893	0.7724		✓	
	2015	--	--	--			
Soil Moisture July (%)	**2014**	0.2608	2.5797	0.0099			✓
	2015	0.3719	3.6367	0.0003			✓
Soil Moisture August (%)	**2014**	0.3838	3.7442	0.0002			✓
	2015	0.2327	2.3132	0.0207			✓
Soil Moisture September (%)	**2014**	0.4760	4.6219	0.0000			✓
	2015	0.2944	2.8938	0.0038			✓
Mean Soil Moisture (%)	**2014**	0.5103	4.9445	0.0000			✓
	2015	0.4447	4.3255	0.0000			✓
Leaf Water Potential July (Mpa)	**2014**	0.0481	0.5710	0.5680		✓	
	2015	-0.1128	-0.1912	0.8483		✓	
Leaf Water Potential August (Mpa)	**2014**	0.6053	5.8048	0.0000			✓
	2015	-0.5455	-1.7118	0.0869	✓		
Leaf Water Potential September (Mpa)	**2014**	-0.1448	-1.2495	0.2115		✓	
	2015	0.1996	0.9120	0.3618		✓	
Mean Leaf Water Potential (Mpa)	**2014**	0.2739	2.7078	0.0068			✓
	2015	-0.0085	0.1865	0.8520		✓	

Table A25 Spatial Autocorrelation (Moran's *I*) results for Coyote's Run (North-South) 2014-2015: Moran's *I* Index values, z-scores and p-value. Patterns are expressed as clustered, dispersed, or random and are indicated for the corresponding attribute (✓), February bud (LT_{50}) was not collected in 2015.

COYOTE'S RUN PINOT NOIR (N-S)							
	Year	**Moran's Index**	**z-score**	**p-value**	**Dispersed**	**Random**	**Clustered**
NDVI July	**2014**	0.1110	1.2400	0.2150		✓	
	2015	0.7509	7.0888	0.0000			✓
NDVI August	**2014**	0.3150	2.9447	0.0032			✓
	2015	0.3595	3.4571	0.0005			✓
NDVI September	**2014**	0.3512	3.2822	0.0010			✓
	2015	0.4294	4.1435	0.0000			✓
Cluster number (per vine)	**2014**	-0.0805	-0.6564	0.5116		✓	
	2015	0.0256	0.3432	0.7315		✓	
Yield (kg/vine)	**2014**	-0.1010	-0.8519	0.3943		✓	
	2015	-0.0529	-0.5404	0.5889		✓	
Cluster weight (kg)	**2014**	-0.1100	-0.9309	0.3519		✓	
	2015	-0.0258	-0.4198	0.6746		✓	
Berry weight (g)	**2014**	0.0729	0.7850	0.4325		✓	
	2015	0.0341	0.4174	0.6764		✓	
Soluble Solids (°Brix)	**2014**	-0.1700	-1.5098	0.1311		✓	
	2015	0.2490	2.3623	0.0182			✓
pH	**2014**	0.1621	1.6120	0.1070		✓	
	2015	0.3424	3.2560	0.0011			✓
Titratable Acidity (g/L)	**2014**	0.1037	1.0737	0.2829		✓	
	2015	0.1112	1.1433	0.2529		✓	
Anthocyanins (mg/L)	**2014**	0.1996	1.9689	0.0490			✓
	2015	0.0905	0.9462	0.3440		✓	
Colour (au)	**2014**	0.1221	1.2496	0.2114		✓	
	2015	0.3893	3.6503	0.0003			✓
Phenols (mg/L)	**2014**	0.0070	0.1693	0.8655		✓	
	2015	0.4167	3.8768	0.0001			✓
Vine size (kg)	**2014**	0.1020	1.0791	0.2805		✓	
	2015	0.0125	0.2230	0.2230		✓	
January Bud LT_{50}	**2014**	-0.0204	-0.0850	0.9323		✓	
	2015	0.2121	1.2892	0.1973		✓	
February Bud LT_{50}	**2014**	-0.2845	-2.5396	0.0111	✓		
	2015	--	--	--			
Mean Bud LT_{50}	**2014**	-0.0996	-0.8188	0.4129		✓	
	2015	--	--	--			
Soil Moisture July (%)	**2014**	0.2122	2.0809	0.0374			✓
	2015	0.3638	3.4881	0.0005			✓
Soil Moisture August (%)	**2014**	0.3138	3.0241	0.0025			✓
	2015	0.3648	3.5022	0.0005			✓
Soil Moisture September (%)	**2014**	0.1977	1.9453	0.0517			✓
	2015	0.2235	2.1933	0.0283			✓
Mean Soil Moisture (%)	**2014**	0.3290	3.1719	0.0015			✓
	2015	0.5300	5.0302	0.0000			✓
Leaf Water Potential July (Mpa)	**2014**	0.2673	2.5942	0.0095			✓
	2015	0.1198	0.6469	0.5177		✓	
Leaf Water Potential August (Mpa)	**2014**	0.1321	1.3283	0.1841		✓	
	2015	0.1901	0.8735	0.3824		✓	
Leaf Water Potential September (Mpa)	**2014**	0.0634	0.6936	0.4879		✓	
	2015	0.4839	1.9205	0.0548			✓
Mean Leaf Water Potential (Mpa)	**2014**	0.1416	1.4391	0.1501		✓	
	2015	0.2579	1.1077	0.2680		✓	

Table A26 Spatial Autocorrelation (Moran's *I*) results for Cave Spring Riesling 2014-2015: Moran's *I* Index values, z-scores and p-value. Patterns are expressed as clustered, dispersed, or random and are indicated for the corresponding attribute (✓), February bud (LT_{50}) was not collected in 2015.

		CAVE SPRING RIESLING					
	Year	**Moran's Index**	**z-score**	**p-value**	**Dispersed**	**Random**	**Clustered**
NDVI July	**2014**	0.0020	0.1305	0.8962		✓	
	2015	0.1797	1.6369	0.1017		✓	
NDVI August	**2014**	0.2687	2.3768	0.0175			✓
	2015	0.4446	3.8406	0.0001			✓
NDVI September	**2014**	-0.0225	-0.0746	0.9405		✓	
	2015	0.1411	1.2983	0.1942		✓	
Cluster number (per	**2014**	0.2107	1.8729	0.0611			✓
	2015	0.1300	1.2057	0.2279		✓	
Yield (kg/vine)	**2014**	0.1316	1.2074	0.2273		✓	
	2015	0.1658	1.4910	0.1360		✓	
Cluster weight (kg)	**2014**	0.0847	0.8437	0.3988		✓	
	2015	0.1519	1.3788	0.1680		✓	
Berry weight (g)	**2014**	0.2129	1.8957	0.0580			✓
	2015	0.2286	2.0169	0.0437			✓
Soluble Solids (°Brix)	**2014**	-0.0050	0.0720	0.9426		✓	
	2015	0.0232	0.3171	0.7512		✓	
pH	**2014**	0.3555	3.0715	0.0021			✓
	2015	0.2020	1.8123	0.0699			✓
Titratable Acidity (g/L)	**2014**	0.1199	1.1121	0.2661		✓	
	2015	0.0277	0.3463	0.7291		✓	
Free Volatile Terpenes (FVT) (mg/L)	**2014**	-0.0859	-0.6020	0.5471		✓	
	2015	0.6928	5.8461	0.0000			✓
Potentially-Volatile Terpenes (PVT) (mg/L)	**2014**	0.3200	2.7630	0.0057			✓
	2015	0.2032	1.8253	0.0680			✓
Vine size (kg)	**2014**	0.0552	0.5766	0.5642		✓	
	2015	0.1883	1.6783	0.0933			✓
January Bud LT_{50}	**2014**	0.4432	3.7918	0.0002			✓
	2015	-0.2123	-0.6959	0.4865		✓	
February Bud LT_{50}	**2014**	0.2357	2.0659	0.0388			✓
	2015	--	--	--			
Mean Bud LT_{50}	**2014**	0.2193	1.9245	0.0543			✓
	2015	--	--	--			
Soil Moisture July (%)	**2014**	-0.0768	-0.5292	0.5967		✓	
	2015	-0.1017	-0.7423	0.4579		✓	
Soil Moisture August (%)	**2014**	0.1111	1.0359	0.3002		✓	
	2015	-0.1975	-1.5349	0.1248		✓	
Soil Moisture September (%)	**2014**	-0.0651	-0.4298	0.6673		✓	
	2015	-0.0148	-0.0109	0.9913		✓	
Mean Soil Moisture (%)	**2014**	0.0607	0.6175	0.5369		✓	
	2015	-0.2950	-2.3440	0.0191	✓		
Leaf Water Potential July (Mpa)	**2014**	-0.2479	-1.9541	0.0507	✓		
	2015	-0.4644	-1.6001	0.1096		✓	
Leaf Water Potential August (Mpa)	**2014**	0.1258	1.1529	0.2489		✓	
	2015	-0.4300	-1.4438	0.1488		✓	
Leaf Water Potential September (Mpa)	**2014**	0.2011	1.7817	0.0748			✓
	2015	-0.3984	-1.3093	0.1904		✓	
Mean Leaf Water Potential (Mpa)	**2014**	-0.0420	0.2365	0.8130		✓	
	2015	-0.5616	-1.9326	0.0533	✓		

Table A27 Spatial Autocorrelation (Moran's *I*) results for Lambert Riesling 2014-2015: Moran's *I* Index values, z-scores and p-value. Patterns are expressed as clustered, dispersed, or random and are indicated for the corresponding attribute (✓), vine size and January bud (LT_{50}) were only collected in 2015.

LAMBERT RIESLING							
	Year	**Moran's Index**	**z-score**	**p-value**	**Dispersed**	**Random**	**Clustered**
NDVI July	**2014**	0.4697	3.9148	0.0001			✓
	2015	0.4460	3.7199	0.0002			✓
NDVI August	**2014**	0.5501	4.5658	0.0000			✓
	2015	0.2212	1.8973	0.0578			✓
NDVI September	**2014**	0.6111	5.0769	0.0000			✓
	2015	0.6683	5.5175	0.0000			✓
Cluster number (per vine)	**2014**	0.0476	0.5035	0.6146		✓	
	2015	-0.1073	-0.7659	0.4438		✓	
Yield (kg/vine)	**2014**	-0.1146	-0.8188	0.4129		✓	
	2015	-0.2366	-1.8205	0.0687	✓		
Cluster weight (kg)	**2014**	0.4489	3.7462	0.0002			✓
	2015	-0.0600	-0.4073	0.6838		✓	
Berry weight (g)	**2014**	0.0078	0.1739	0.8619		✓	
	2015	0.0406	0.4392	0.6605		✓	
Soluble Solids (°Brix)	**2014**	0.0913	0.8569	0.3915		✓	
	2015	0.0165	0.2533	0.8000		✓	
pH	**2014**	0.0205	0.2772	0.7817		✓	
	2015	-0.1130	-0.8133	0.4161		✓	
Titratable Acidity (g/L)	**2014**	0.0729	0.7016	0.4830		✓	
	2015	-0.0244	-0.0882	0.9297		✓	
Free Volatile Terpenes (FVT) (mg/L)	**2014**	0.2525	2.1521	0.0314			✓
	2015	0.3160	2.6591	0.0078			✓
Potentially-Volatile Terpenes (PVT) (mg/L)	**2014**	0.2013	1.7472	0.0806			✓
	2015	0.4187	3.4956	0.0005			✓
Vine size (kg)	**2014**	--	--	--			
	2015	0.0651	0.6435	0.5199		✓	
January Bud LT_{50}	**2014**	--	--	--			
	2015	0.0640	0.9880	0.3231		✓	
February Bud LT_{50}	**2014**	--	--	--			
	2015	--	--	--			
Mean Bud LT_{50}	**2014**	--	--	--			
	2015	--	--	--			
Soil Moisture July (%)	**2014**	0.0573	0.5768	0.5641		✓	
	2015	0.4457	3.7169	0.0002			✓
Soil Moisture August (%)	**2014**	0.2528	2.1614	0.0307			✓
	2015	0.3608	3.0584	0.0022			✓
Soil Moisture September (%)	**2014**	0.0752	0.7177	0.4729		✓	
	2015	0.2195	1.9054	0.0567			✓
Mean Soil Moisture (%)	**2014**	0.2965	2.5255	0.0116			✓
	2015	0.4931	4.1111	0.0000			✓
Leaf Water Potential July (Mpa)	**2014**	0.3678	3.0829	0.0021			✓
	2015	-0.2535	-0.8201	0.4122		✓	
Leaf Water Potential August (Mpa)	**2014**	0.3986	3.3300	0.0009			✓
	2015	0.0840	0.6154	0.5383		✓	
Leaf Water Potential September (Mpa)	**2014**	0.1290	1.1511	0.2497		✓	
	2015	0.1771	0.9482	0.3430		✓	
Mean Leaf Water Potential (Mpa)	**2014**	0.4013	3.3502	0.0008			✓
	2015	-0.0074	0.1885	0.8505		✓	

B. FIGURES

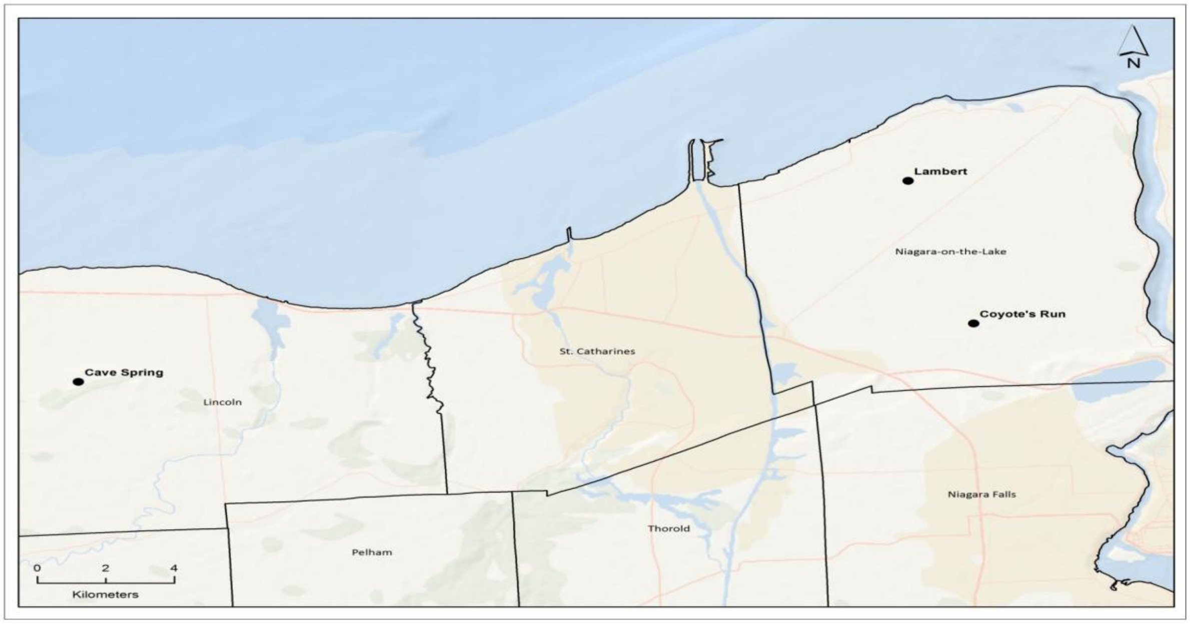

Figure A 1 Study area map of the Niagara Region, Ontario, Canada. Black circles on the map represent the experimental sites; from left to right, Cave Spring vineyards located in Beamsville, Lambert vineyard in Niagara-on-the-Lake, and Coyote's Run winery on the St. David's Bench. Cave Spring and Lambert vineyards contained one Riesling and one Cabernet franc block respectively, and Coyote's Run contained two Pinot noir blocks.

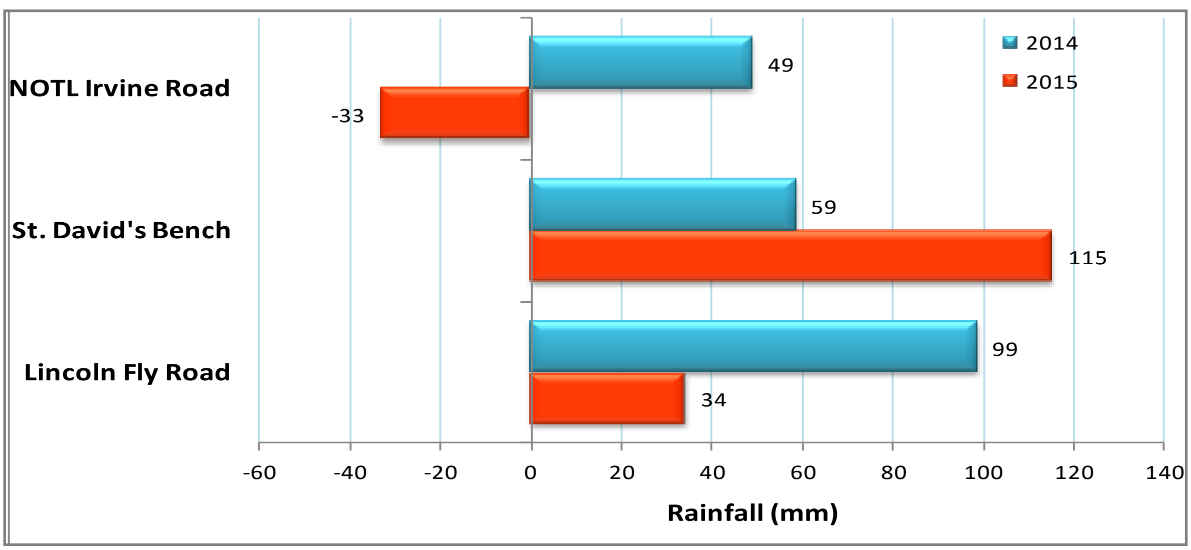

Figure A 2 Seasonal rainfall deviation from the 30-year normal (April 1st - October 31st) at the closest weather stations to the experimental sites in 2014 and 2015. Weather data courtesy from www.weatherinnovations.com

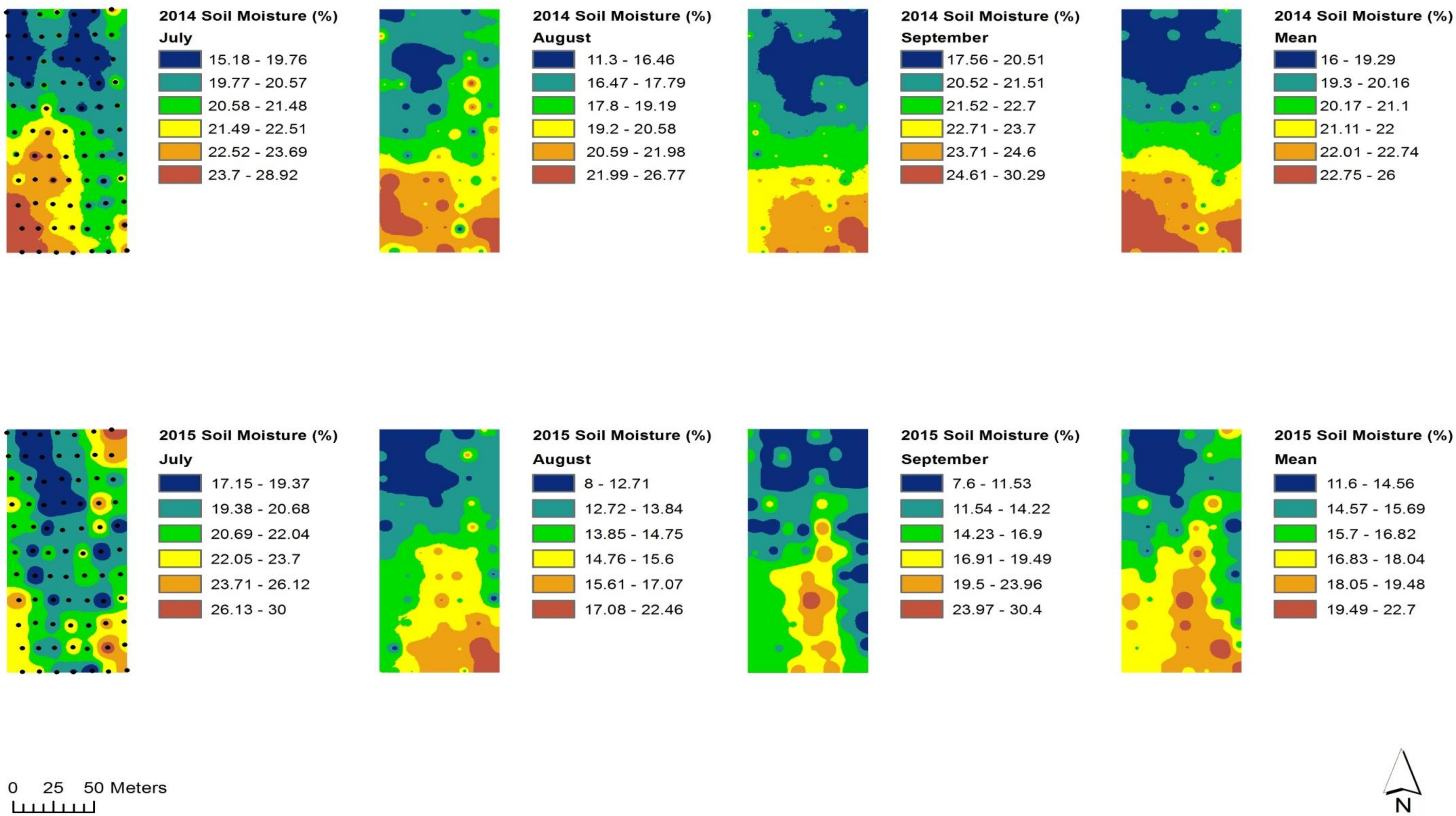

Figure A 3 Maps of soil moisture (%) measurements for the Lambert Cabernet franc in 2014 (top) and 2015 (bottom).

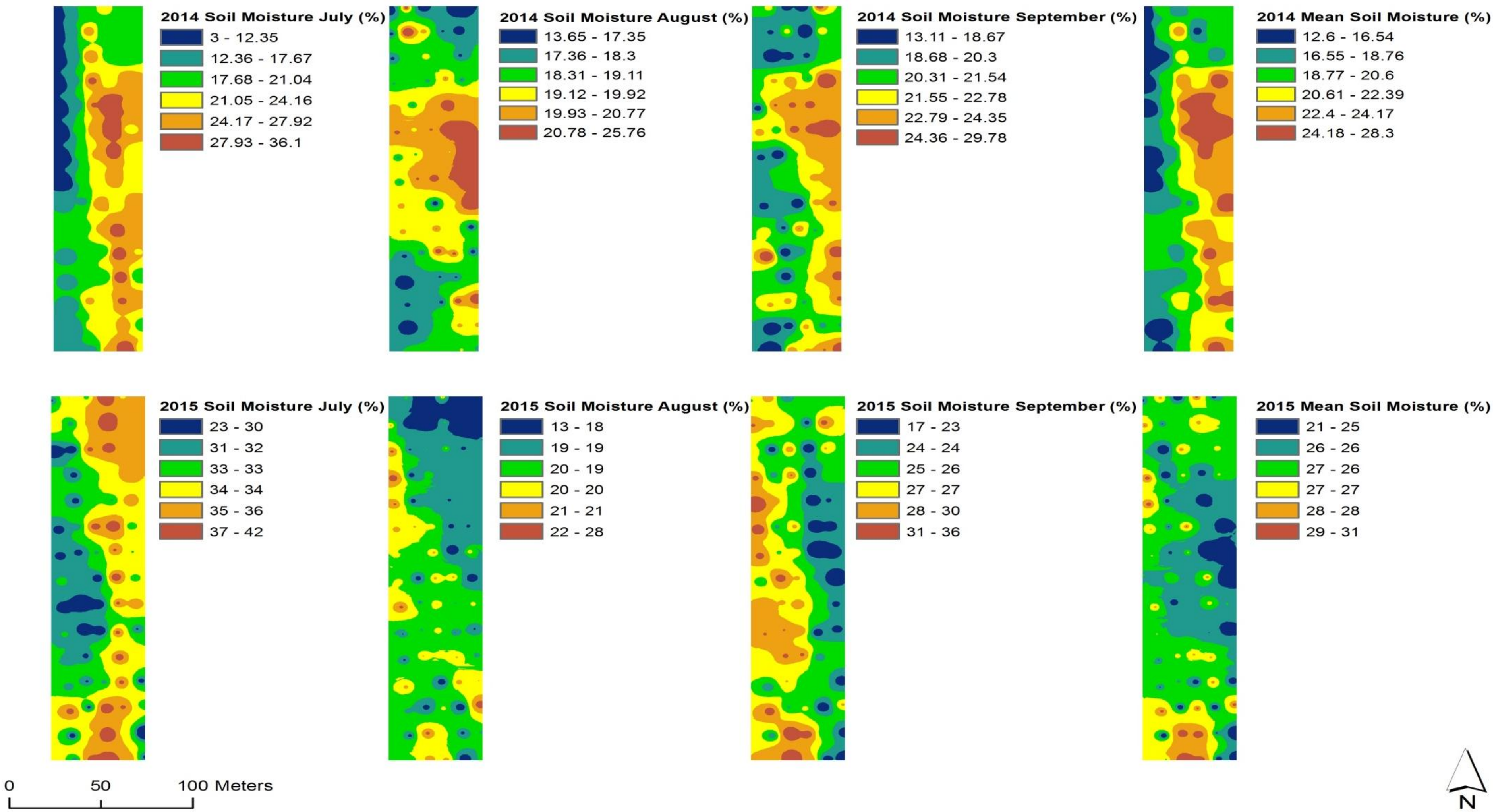

Figure A 4 Maps of soil moisture (%) measurements for the Cave Spring Cabernet franc in 2014 (top) and 2015 (bottom).

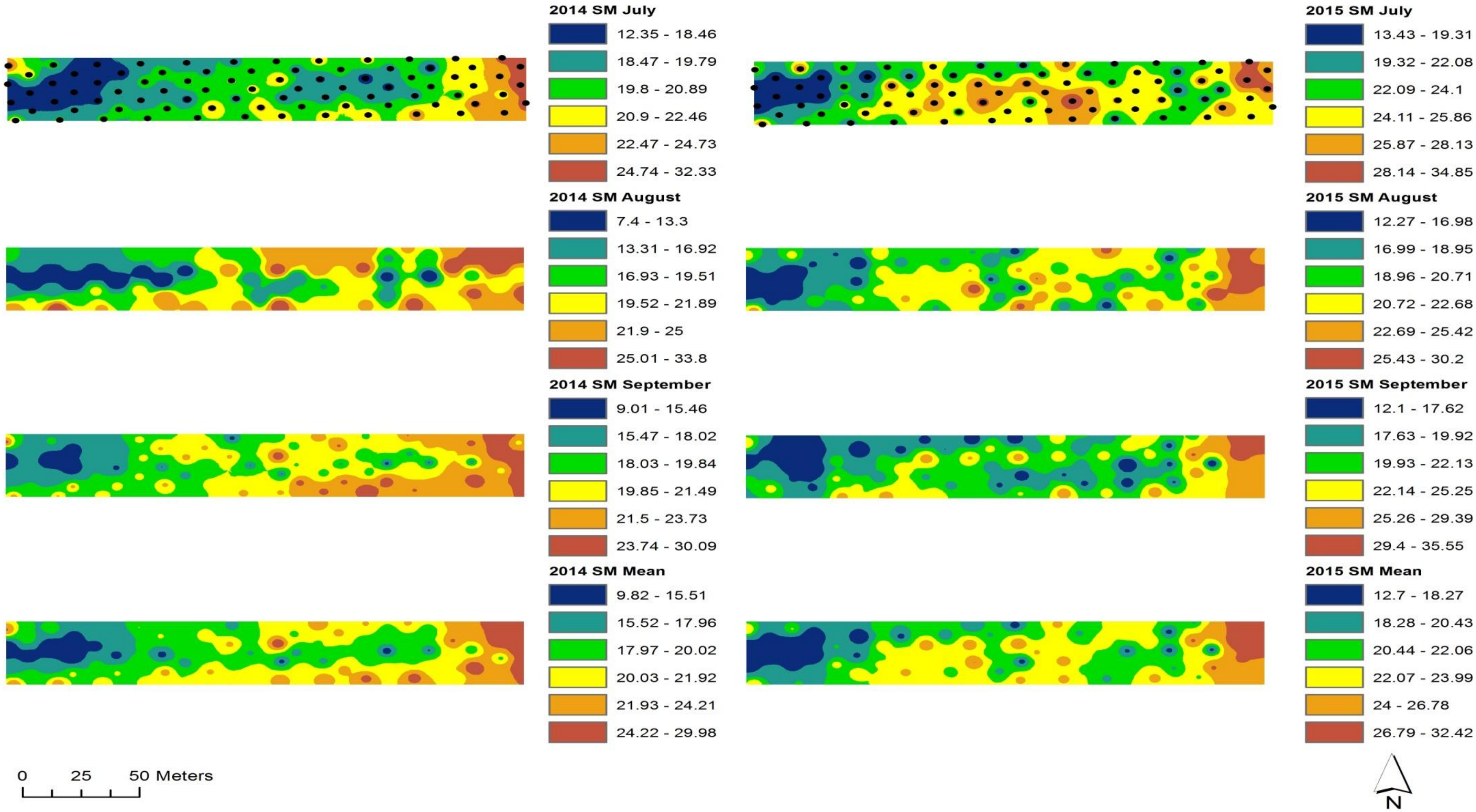

Figure A 5 Maps of soil moisture (%) measurements for the Coyote's Run Pinot noir East-West in 2014 (left) and 2015 (right).

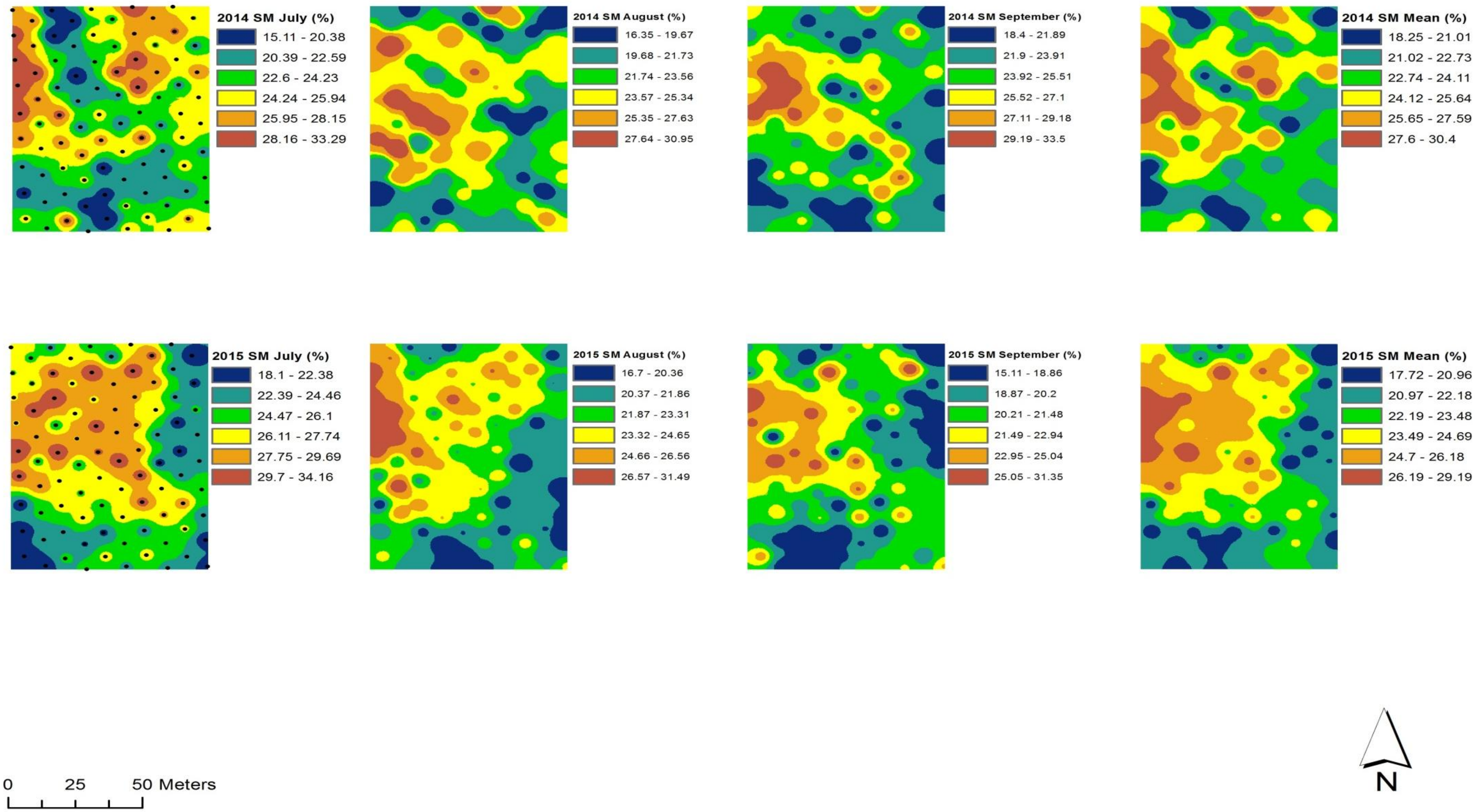

Figure A 6 Maps of soil moisture (%) measurements for the Coyote's Run Pinot noir North-South in 2014 (top) and 2015 (bottom).

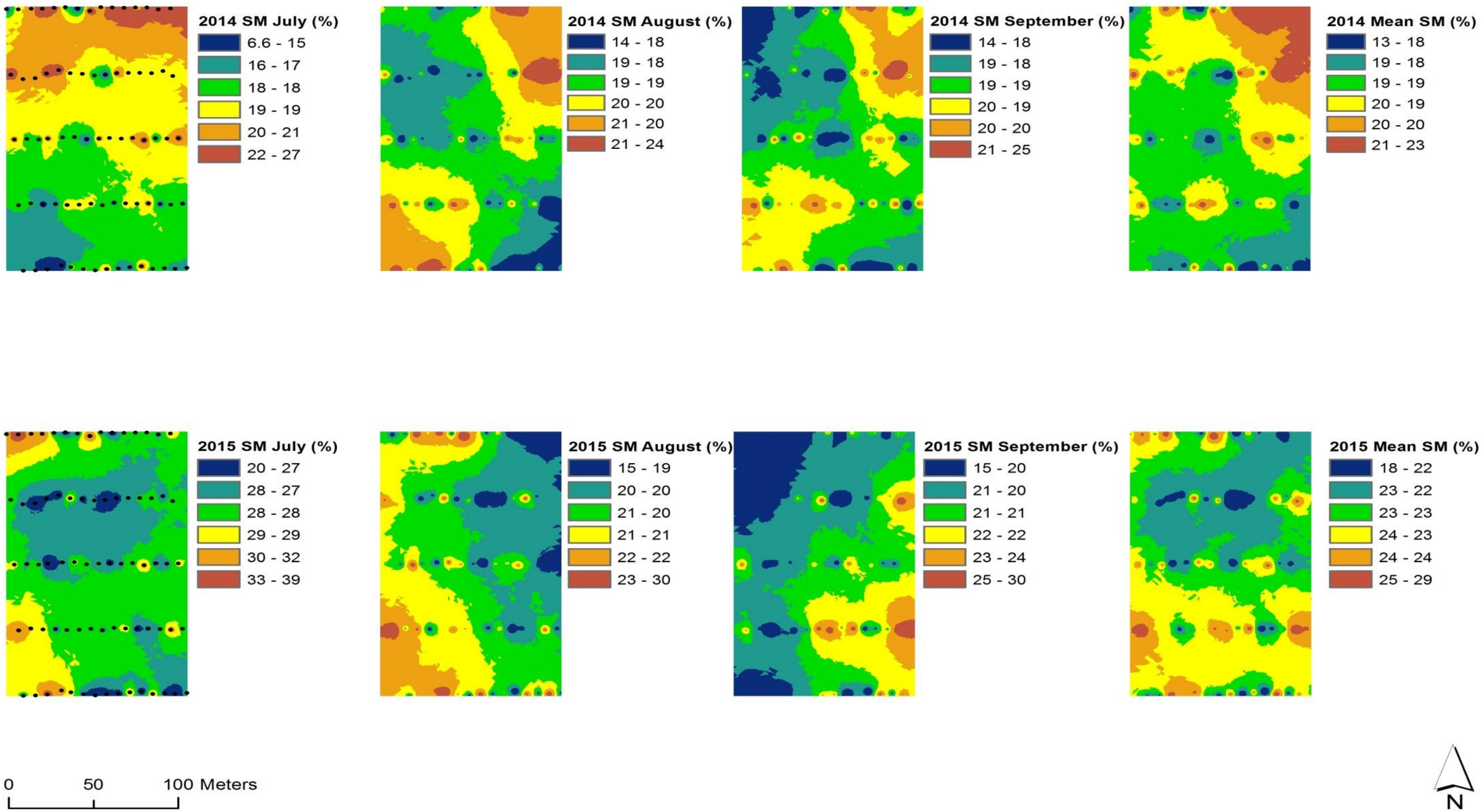

Figure A 7 Maps of soil moisture (%) measurements for the Cave Spring Riesling in 2014 (top) and 2015 (bottom).

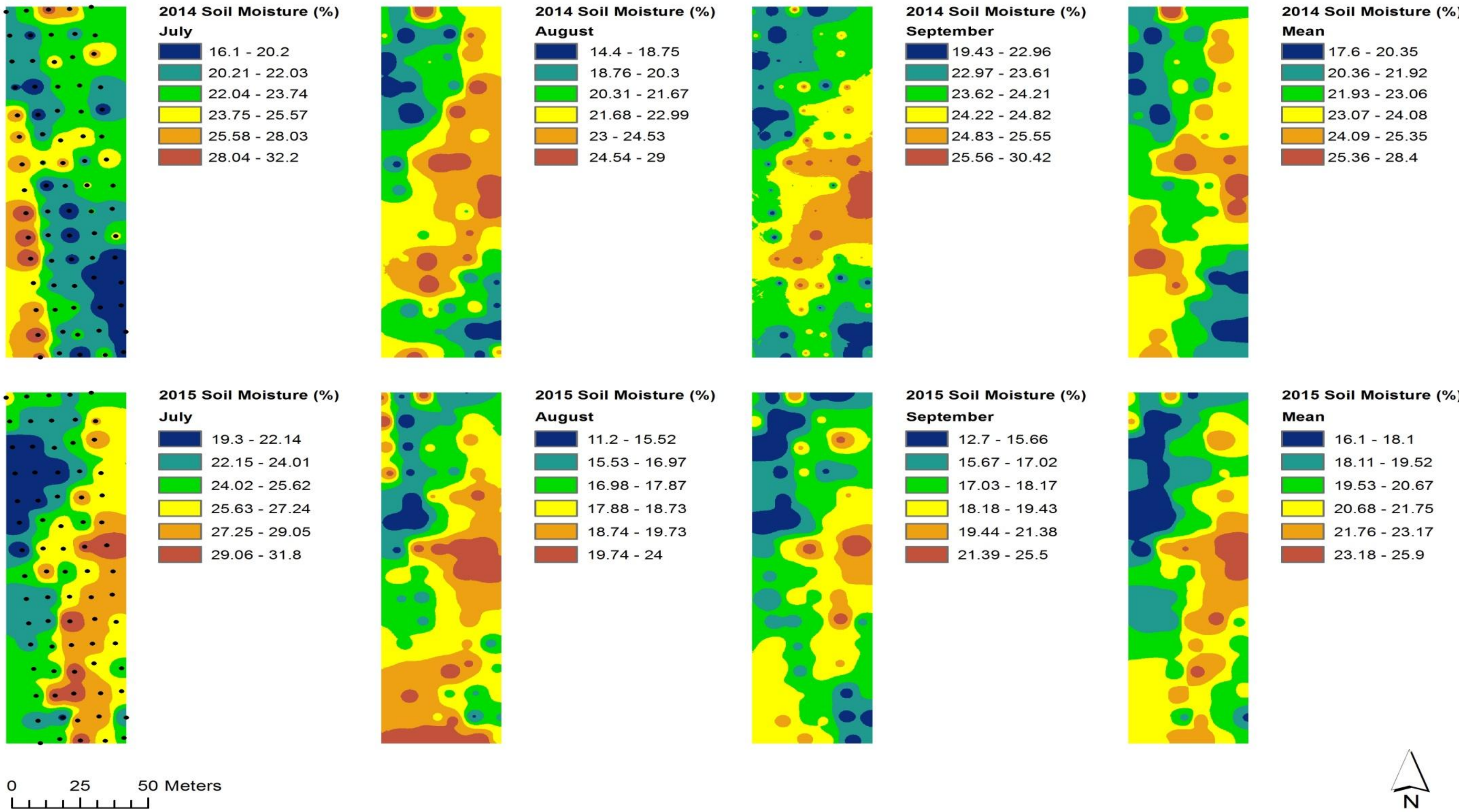

Figure A 8 Maps of soil moisture (%) measurements for the Lambert Riesling in 2014 (top) and 2015 (bottom).

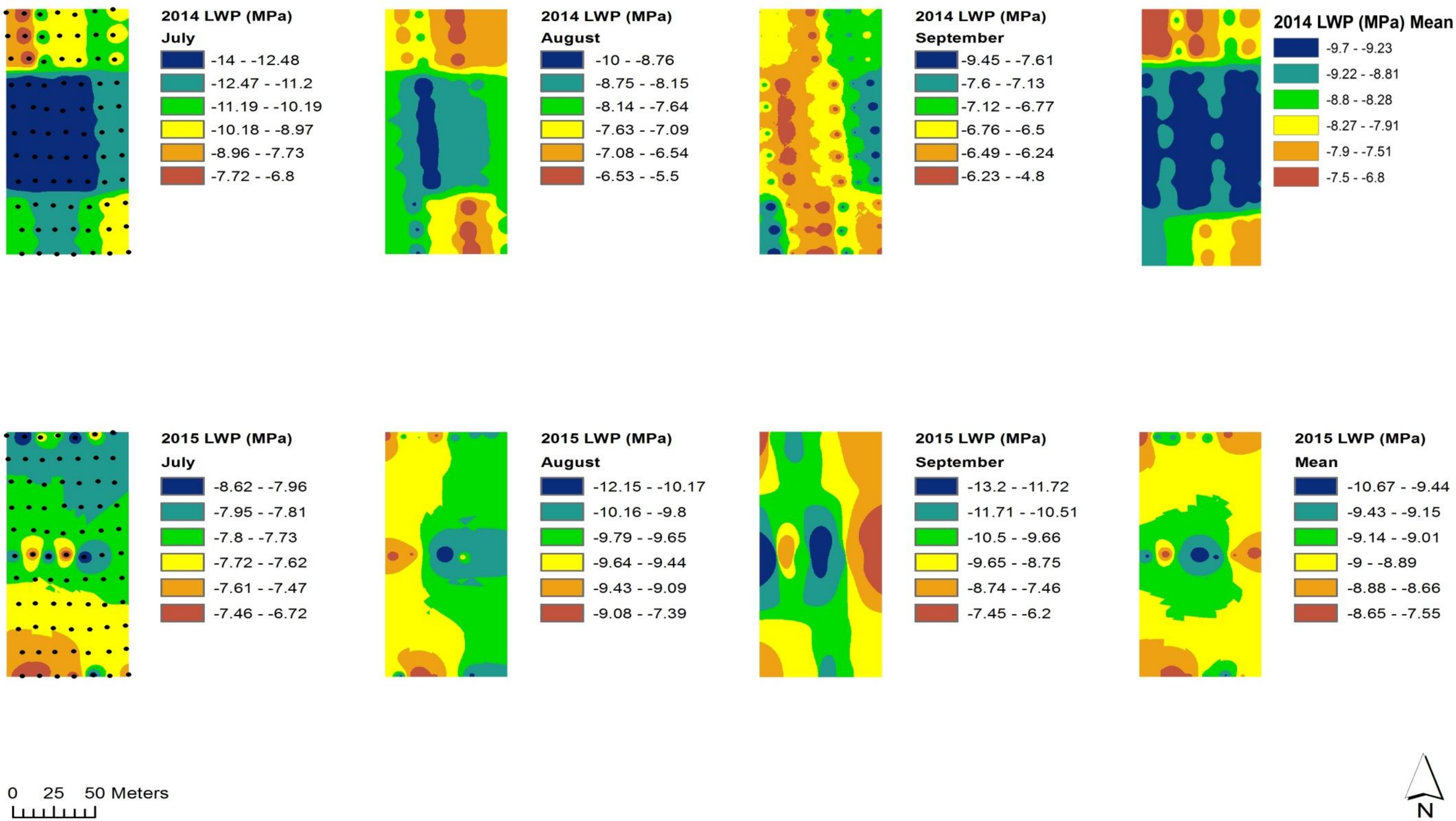

Figure A 9 Maps of leaf water potential (LWP) measurements (-MPa) for the Lambert Cabernet franc in 2014 (top) and 2015 (bottom).

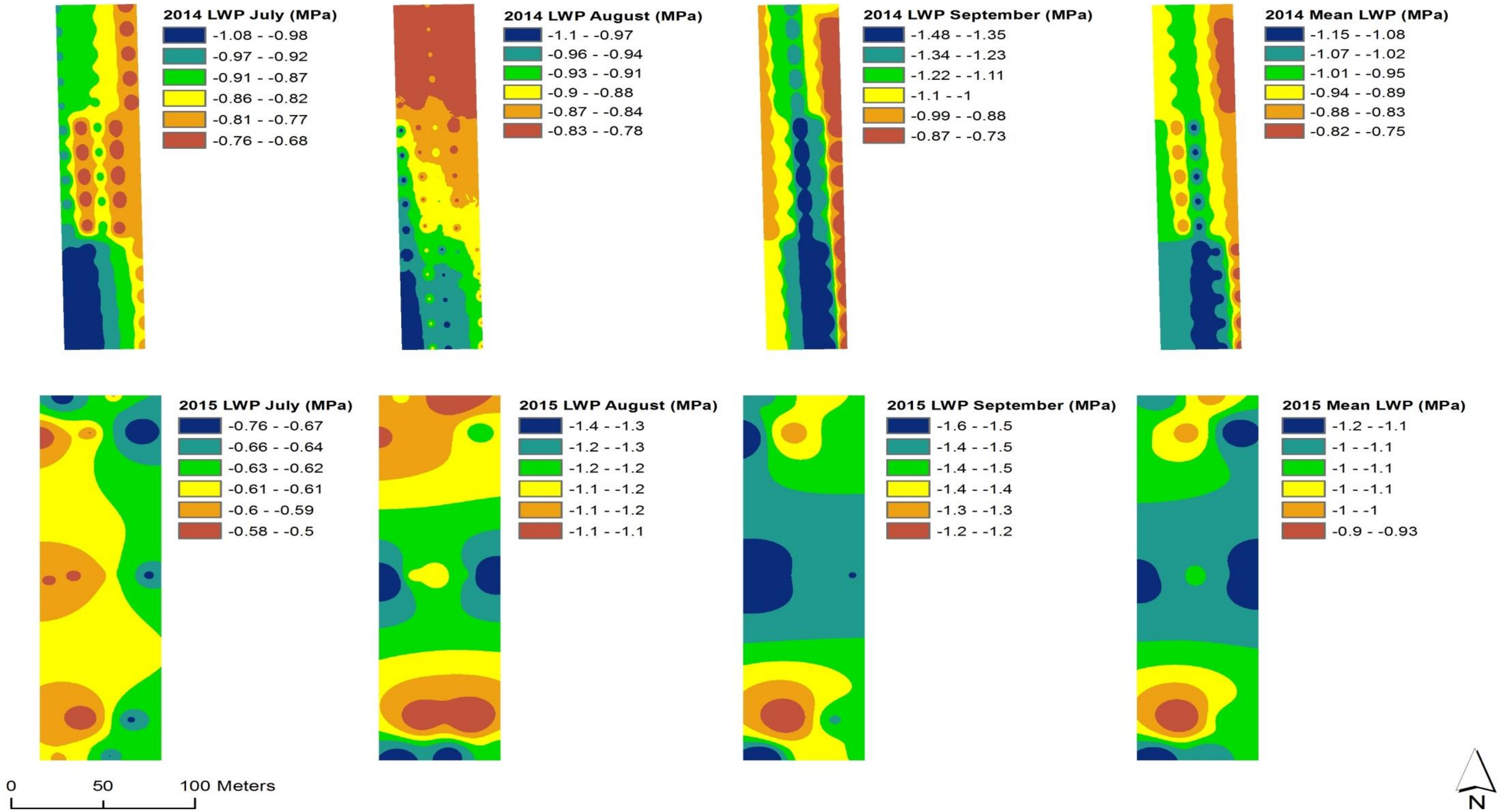

Figure A 10 Maps of leaf water potential (LWP) measurements (-MPa) for the Cave Spring Cabernet franc in 2014 (top) and 2015 (bottom).

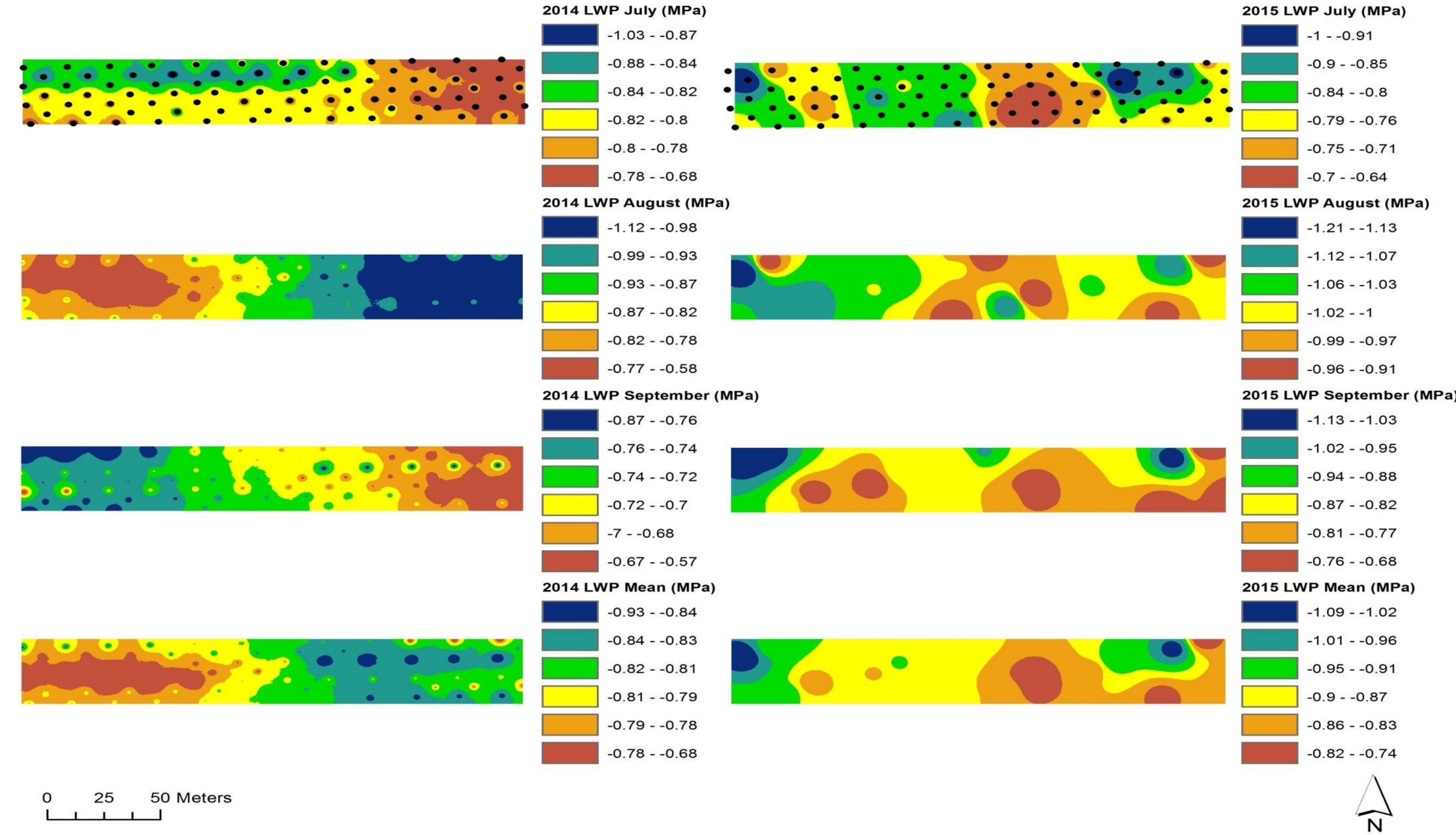

Figure A 11 Maps of leaf water potential (LWP) measurements (-MPa) for the Coyote's Run Pinot noir East West in 2014 (left) and 2015 (right).

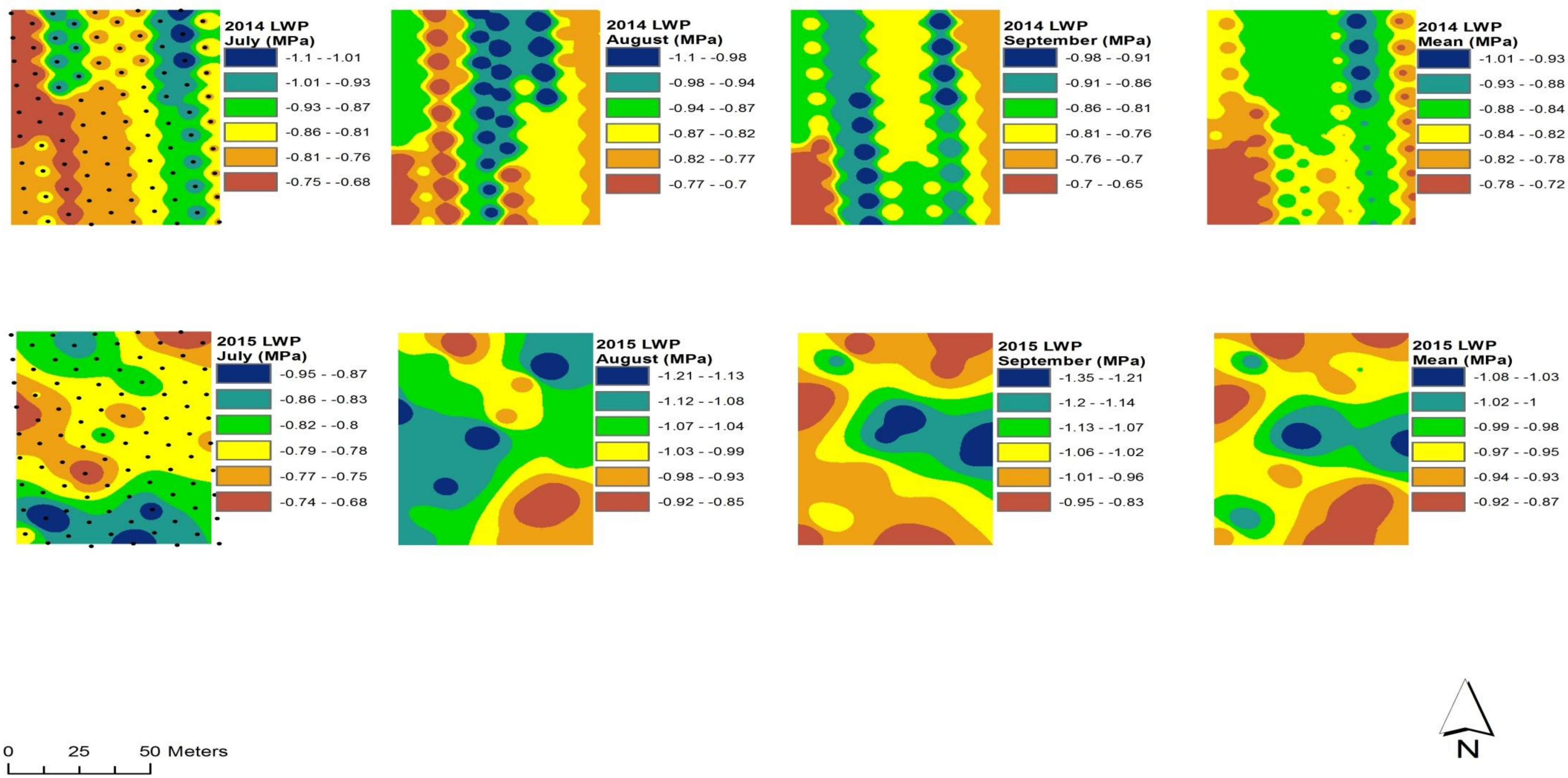

Figure A 12 Maps of leaf water potential (LWP) measurements (-MPa) for the Coyote's Run Pinot noir North South in 2014 (top) and 2015 (bottom).

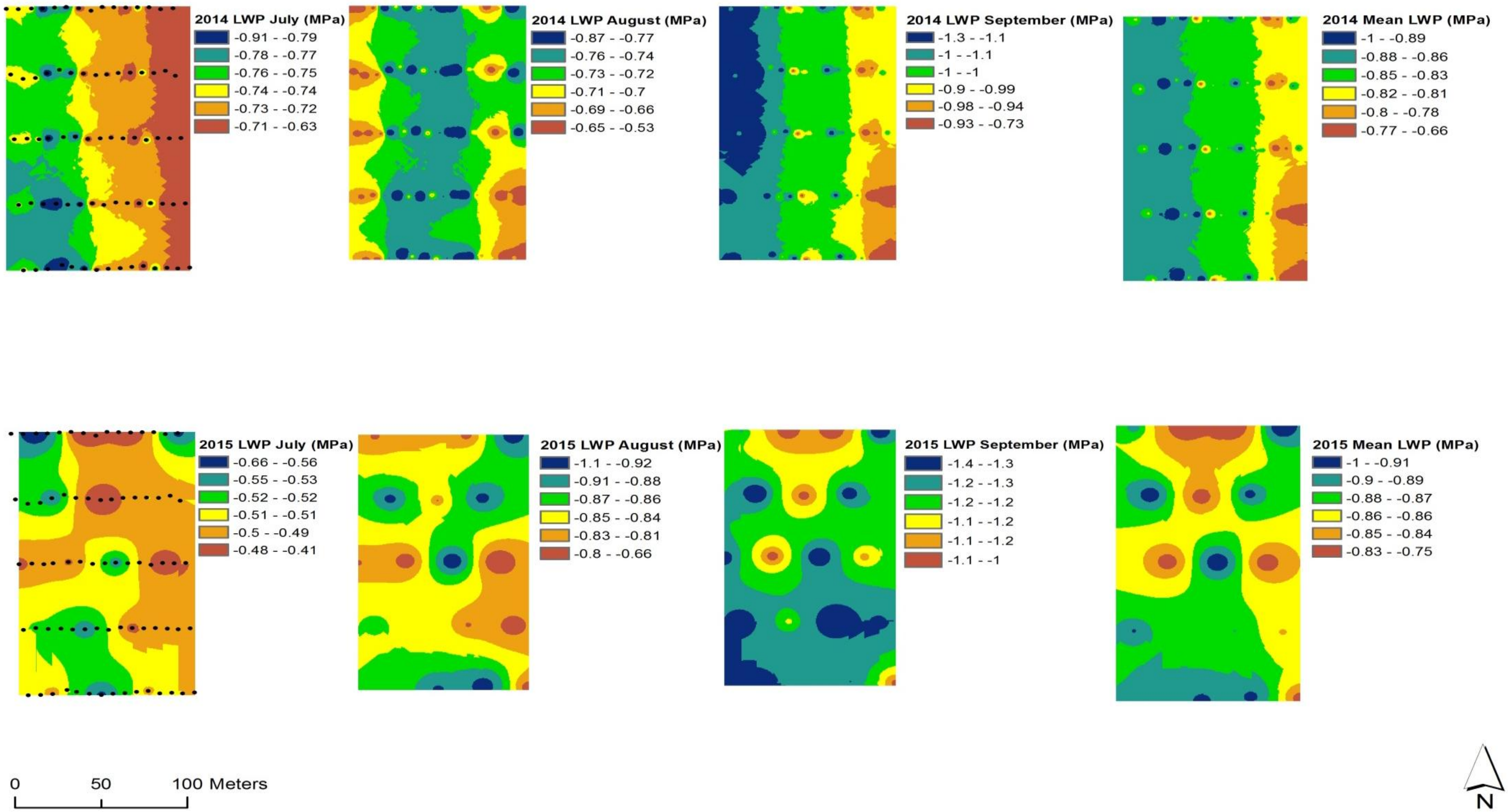

Figure A 13 Maps of leaf water potential (LWP) measurements (-MPa) for the Cave Spring Riesling in 2014 (top) and 2015 (bottom).

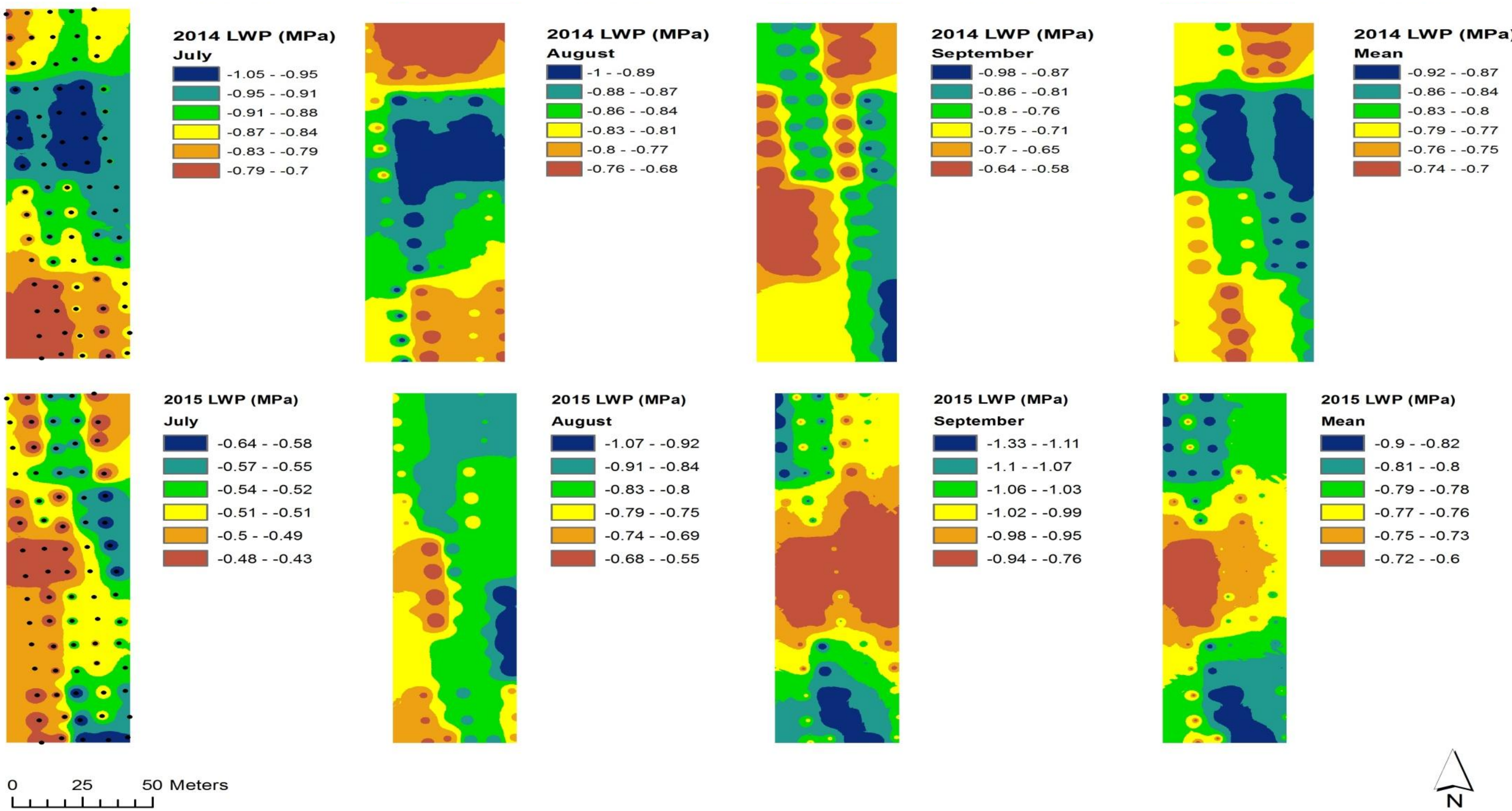

Figure A 14 Maps of leaf water potential (LWP) measurements (-MPa) for the Lambert Riesling in 2014 (top) and 2015 (bottom).

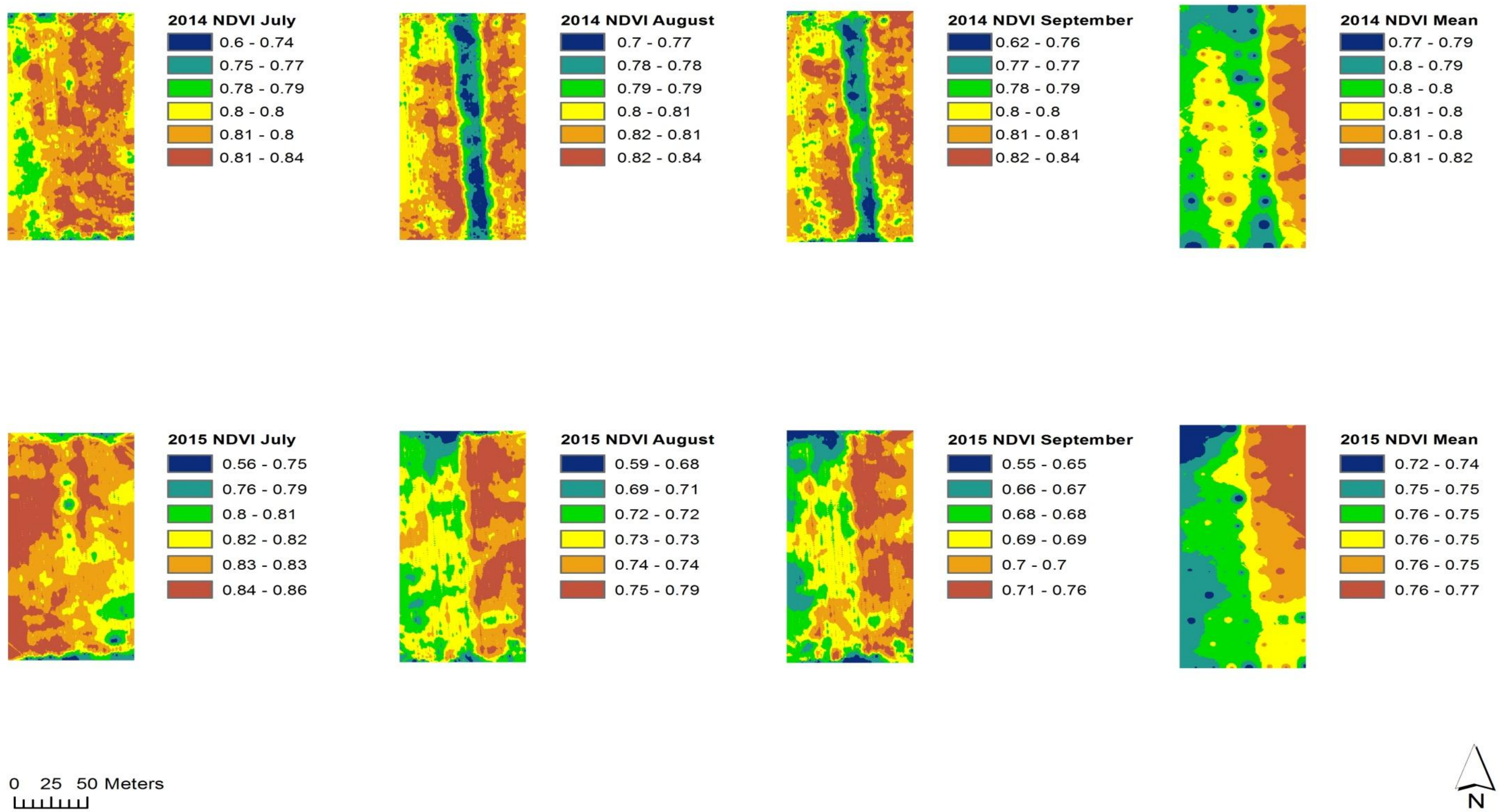

Figure A 15 Maps of NDVI measurements for the Lambert Cabernet franc in 2014 (top) and 2015 (bottom).

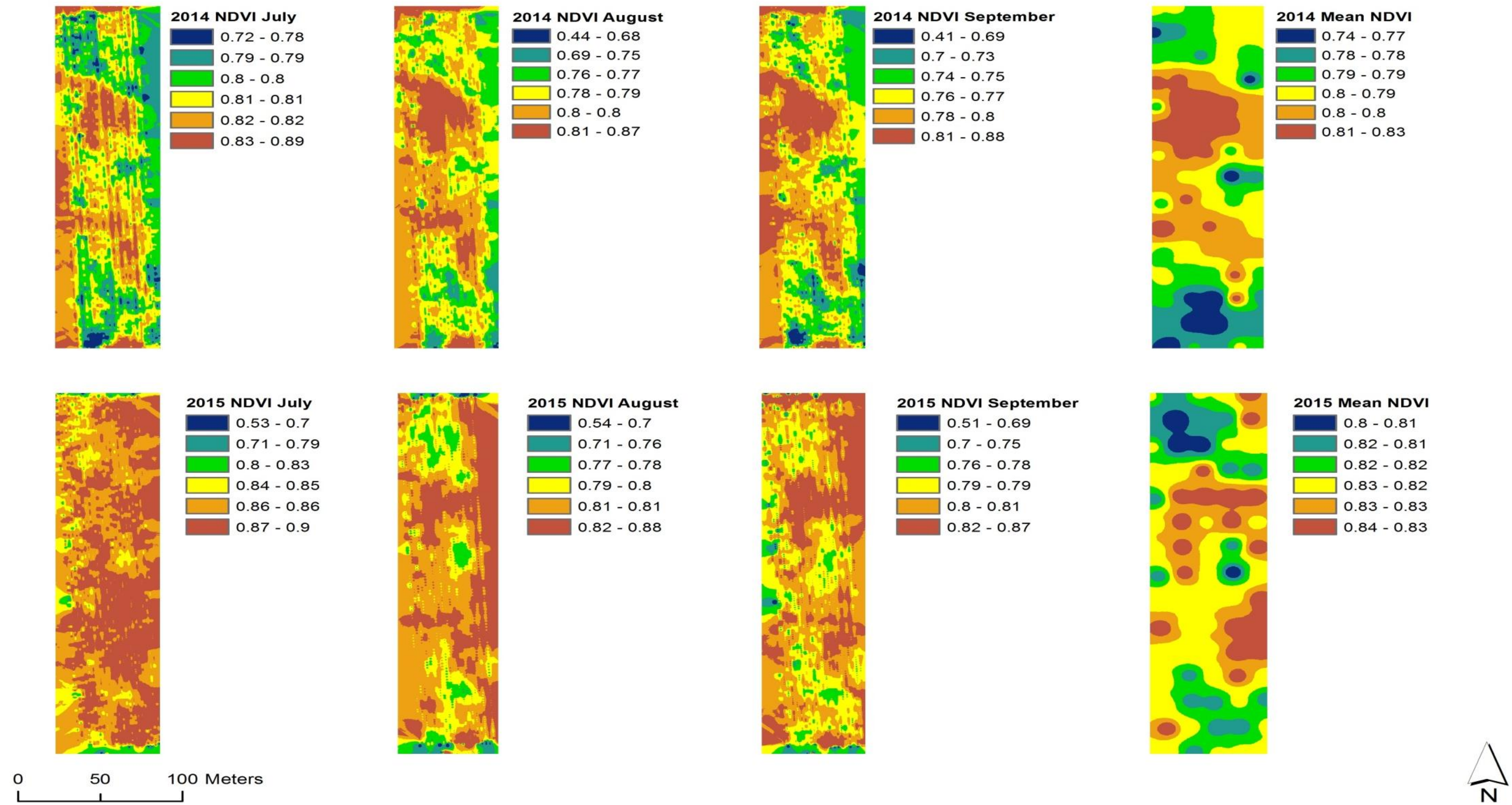

Figure A 16 Maps of NDVI measurements for the Cave Spring Cabernet franc in 2014 (top) and 2015 (bottom).

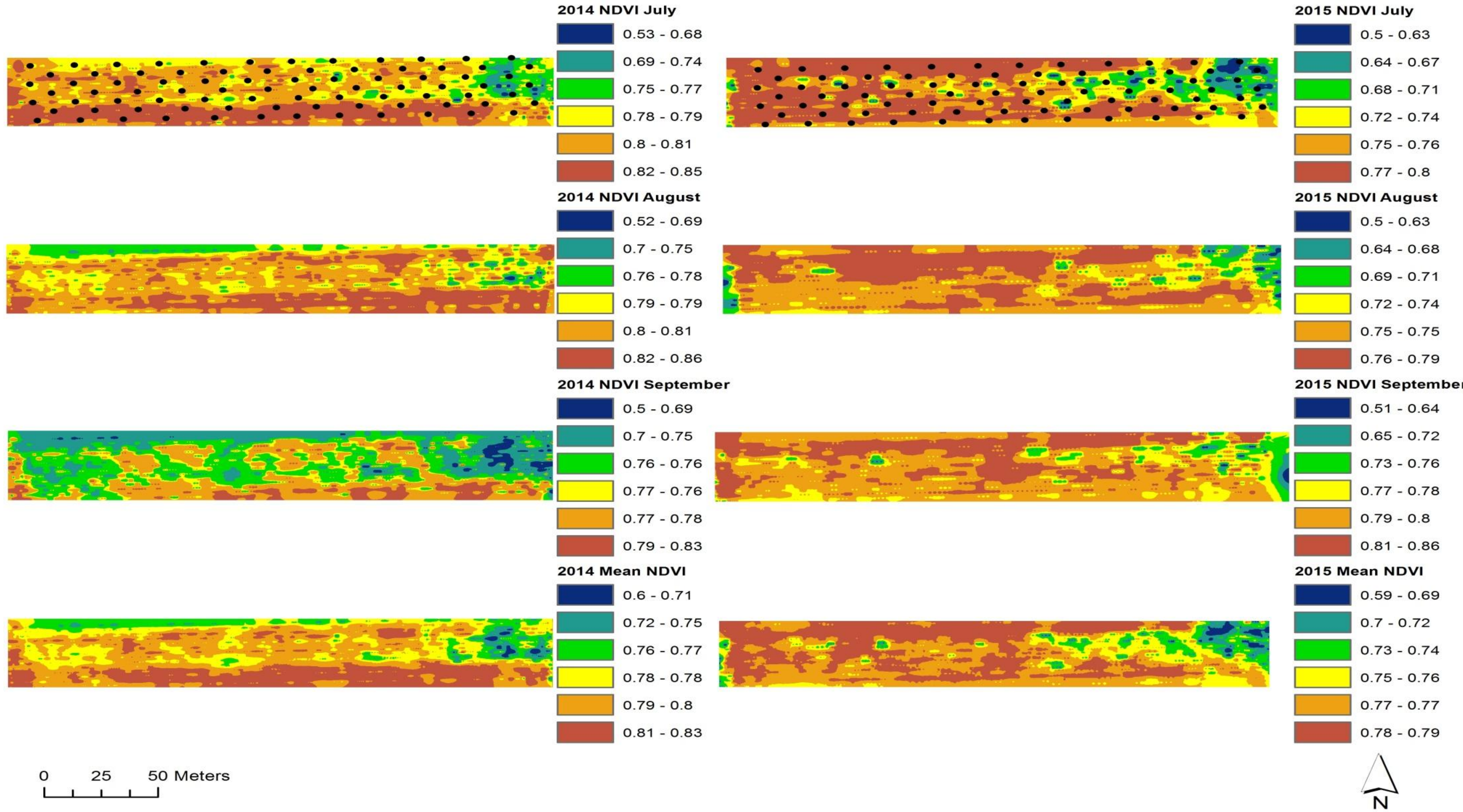

Figure A 17 Maps of NDVI measurements for the Coyote's Run Pinot noir East West in 2014 (left) and 2015 (right).

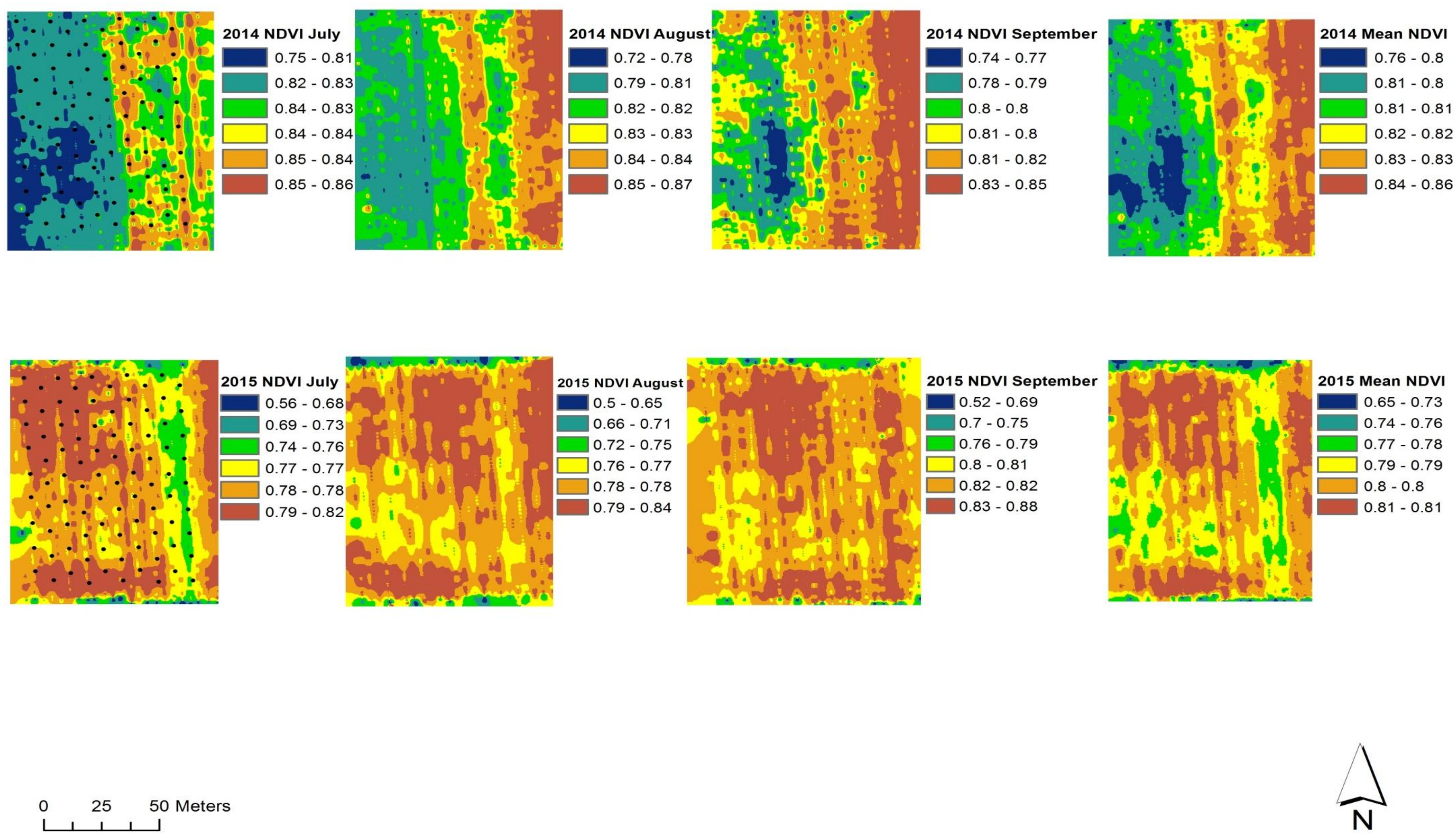

Figure A 18 Maps of NDVI measurements for the Coyote's Run Pinot noir North South in 2014 (top) and 2015 (bottom).

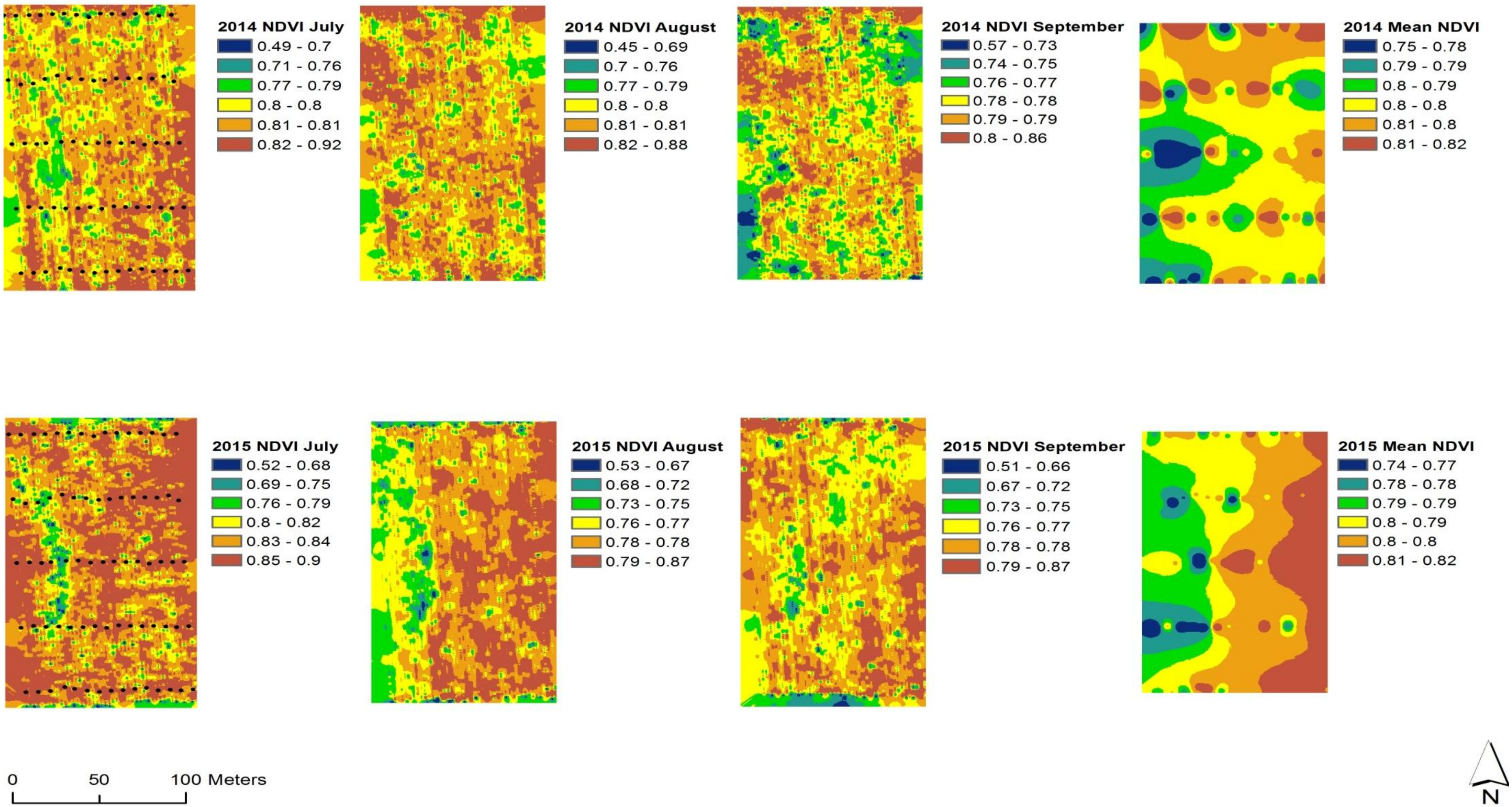

Figure A 19 Maps of NDVI measurements for the Cave Spring Riesling in 2014 (top) and 2015 (bottom).

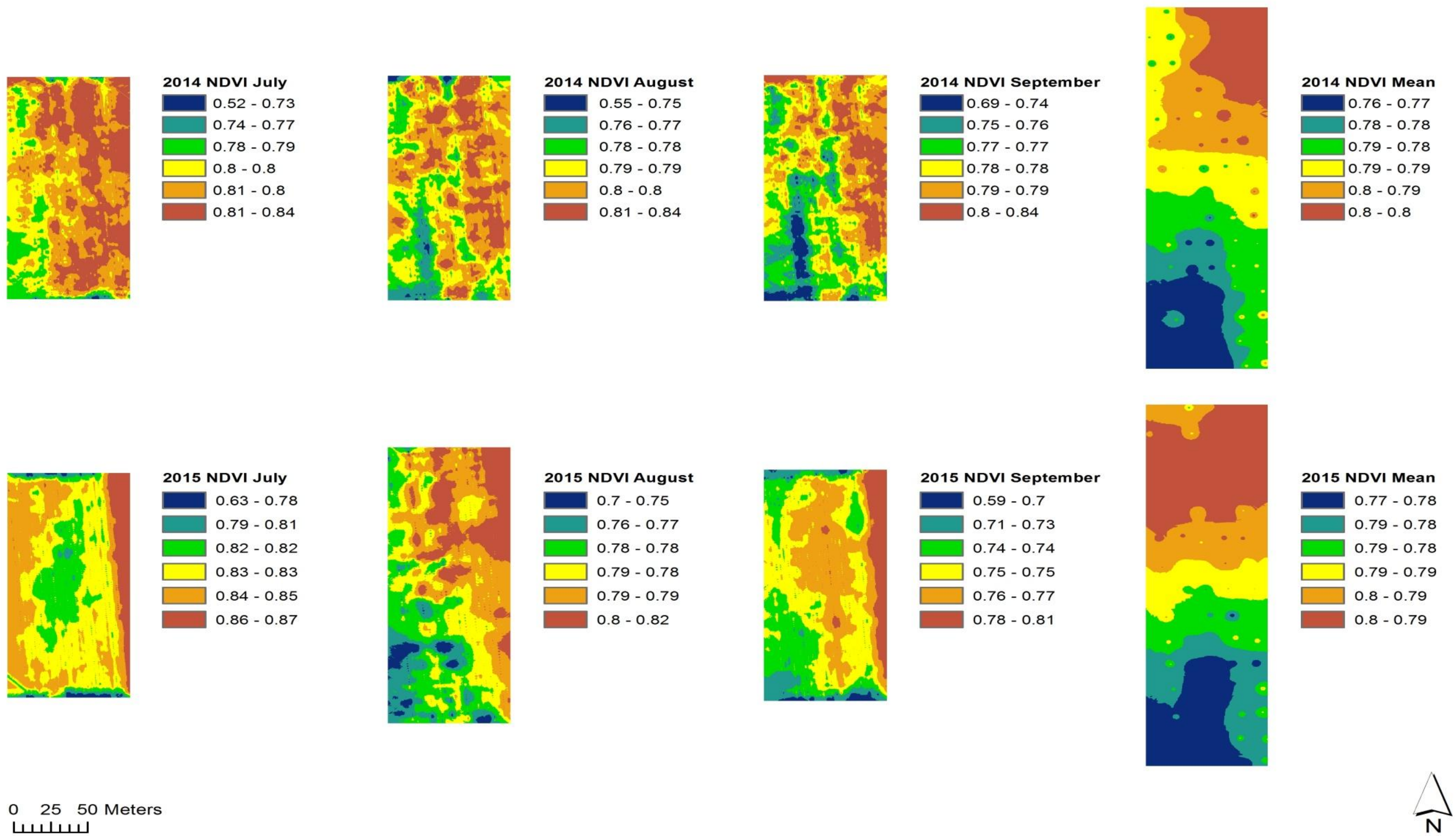

Figure A 20 Maps of NDVI measurements for the Lambert Riesling in 2014 (top) and 2015 (bottom).

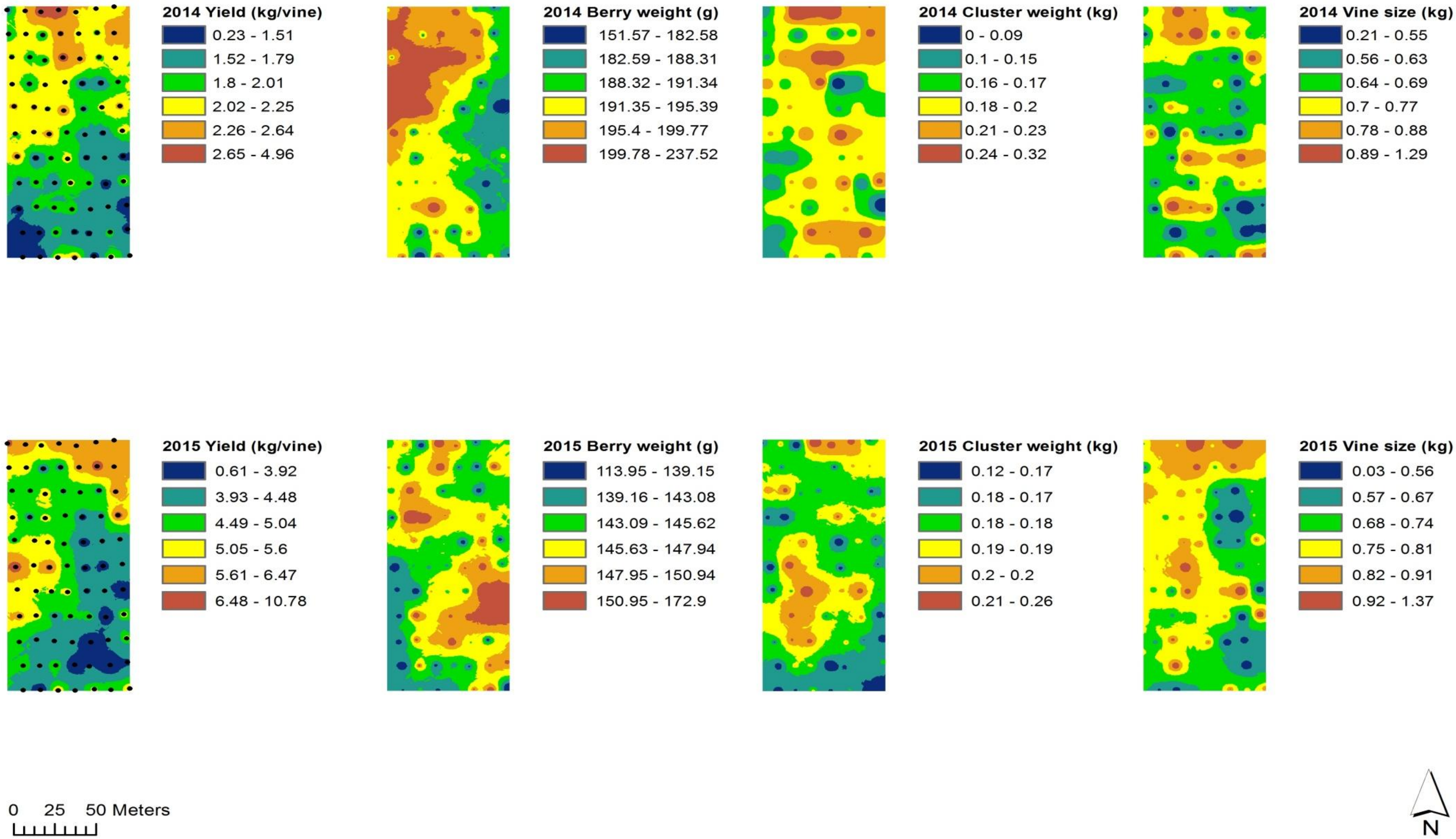

Figure A 21 Maps of yield (kg/vine), berry weight (g), cluster weight (kg), and vine size (kg/vine)for the Lambert Cabernet franc in 2014 (top) and 2015 (bottom).

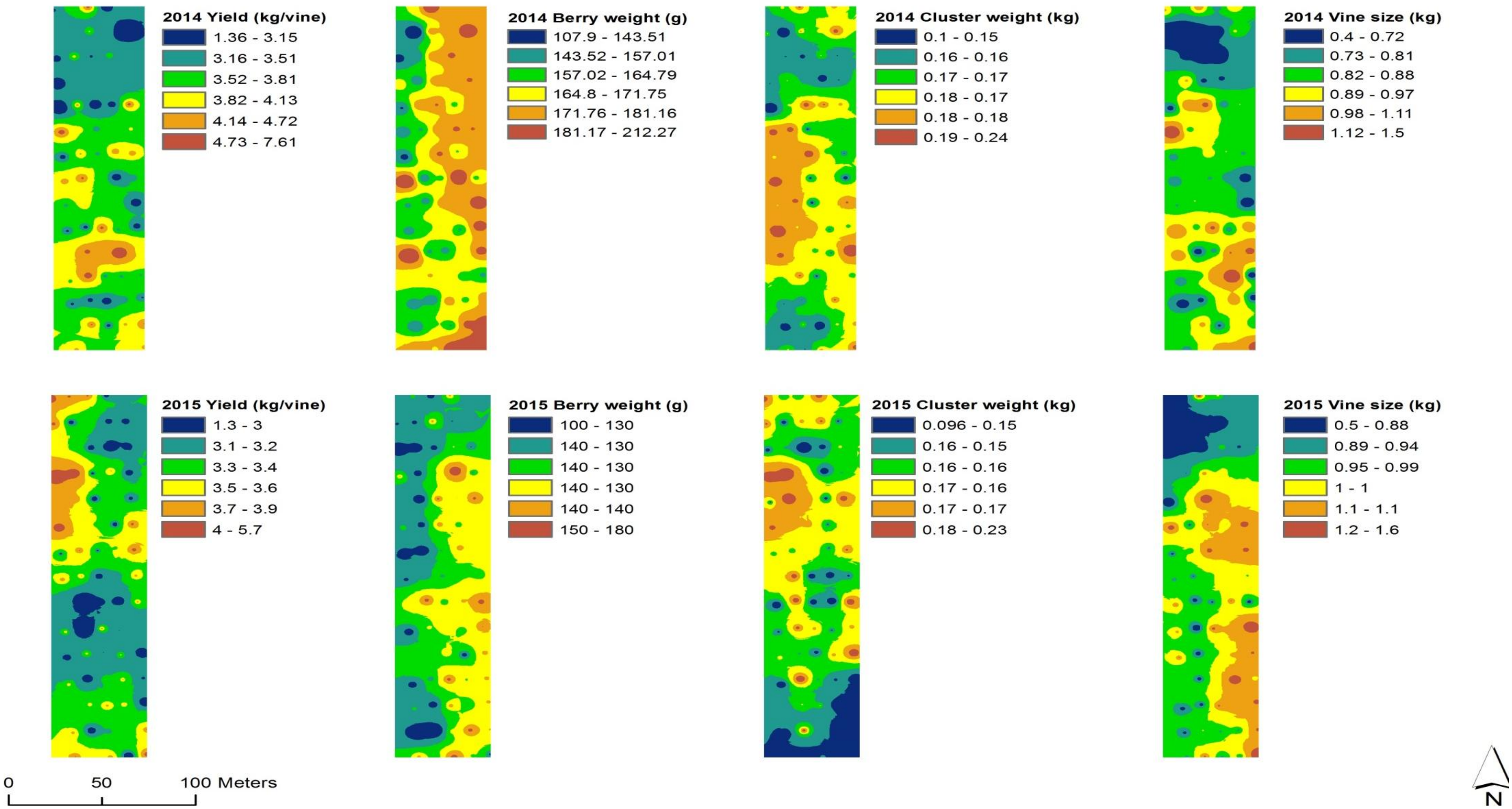

Figure A 22 Maps of yield (kg/vine), berry weight (g), cluster weight (kg), and vine size (kg/vine)for the Cave Spring Cabernet franc in 2014 (top) and 2015 (bottom).

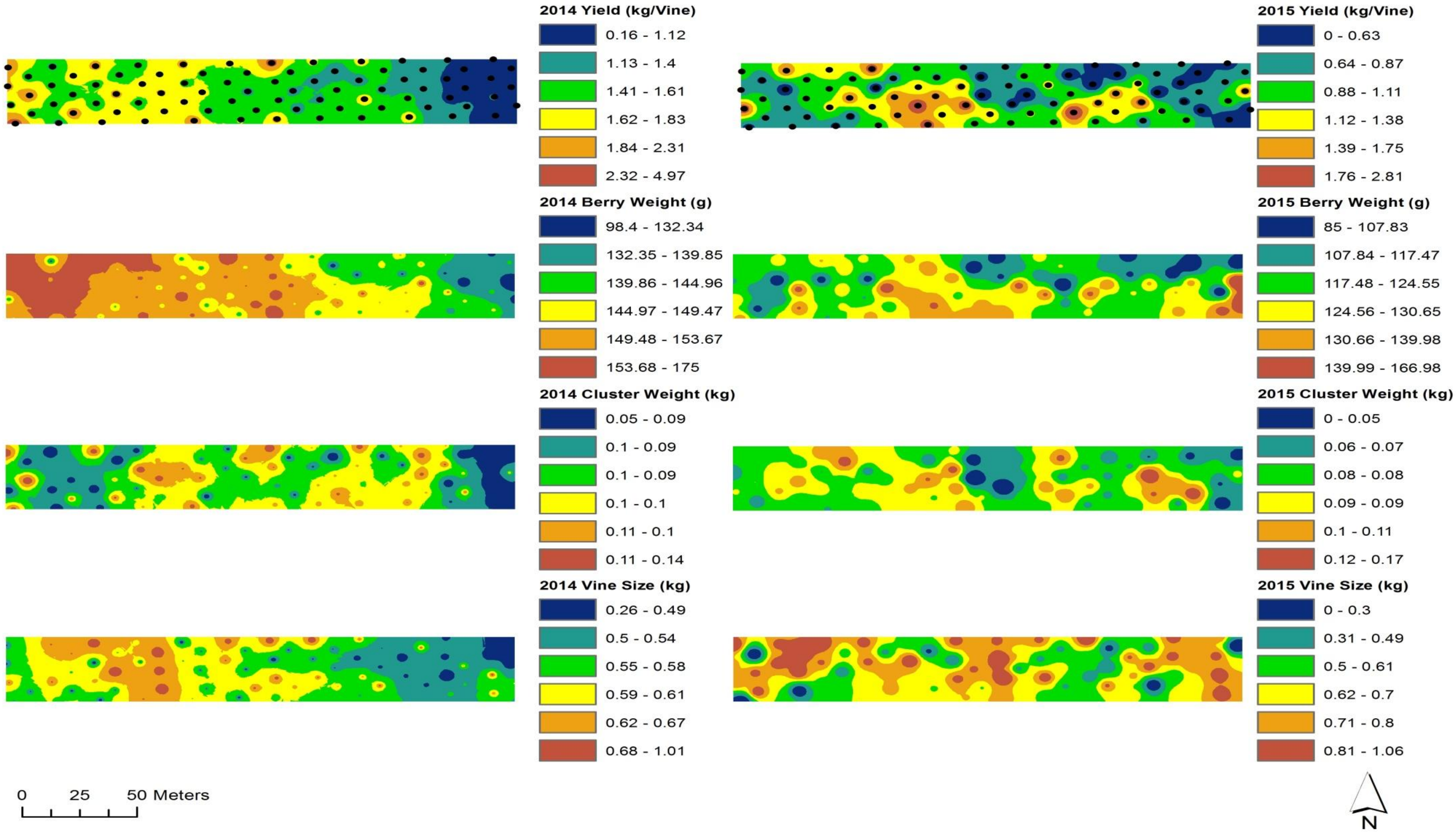

Figure A 23 Maps of yield (kg/vine), berry weight (g), cluster weight (kg), and vine size (kg/vine) for the Coyote's Run Pinot noir East West in 2014 (left) and 2015 (right).

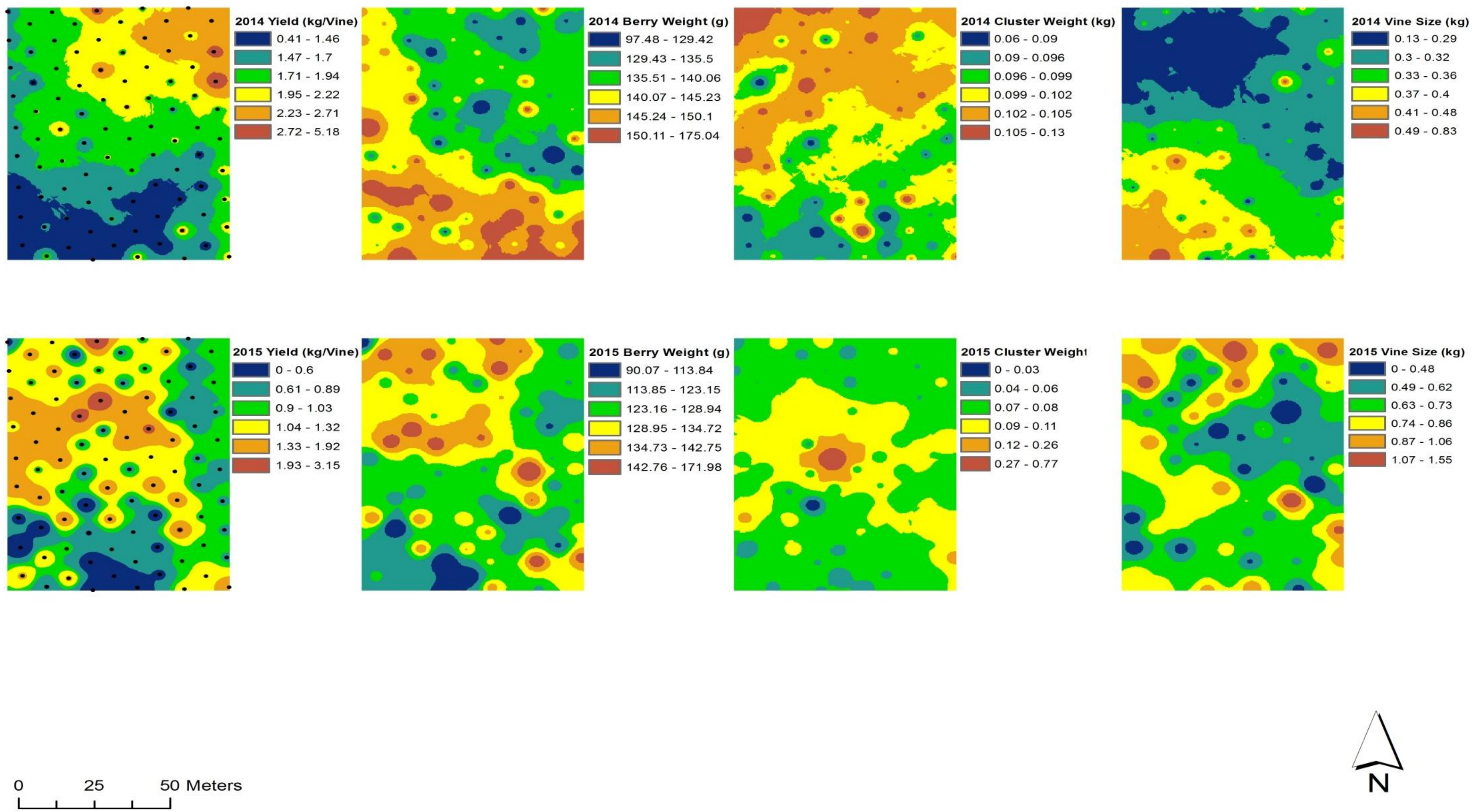

Figure A 24 Maps of yield (kg/vine), berry weight (g), cluster weight (kg), and vine size (kg/vine) for the Coyote's Run Pinot noir North-South in 2014 (top) and 2015 (bottom).

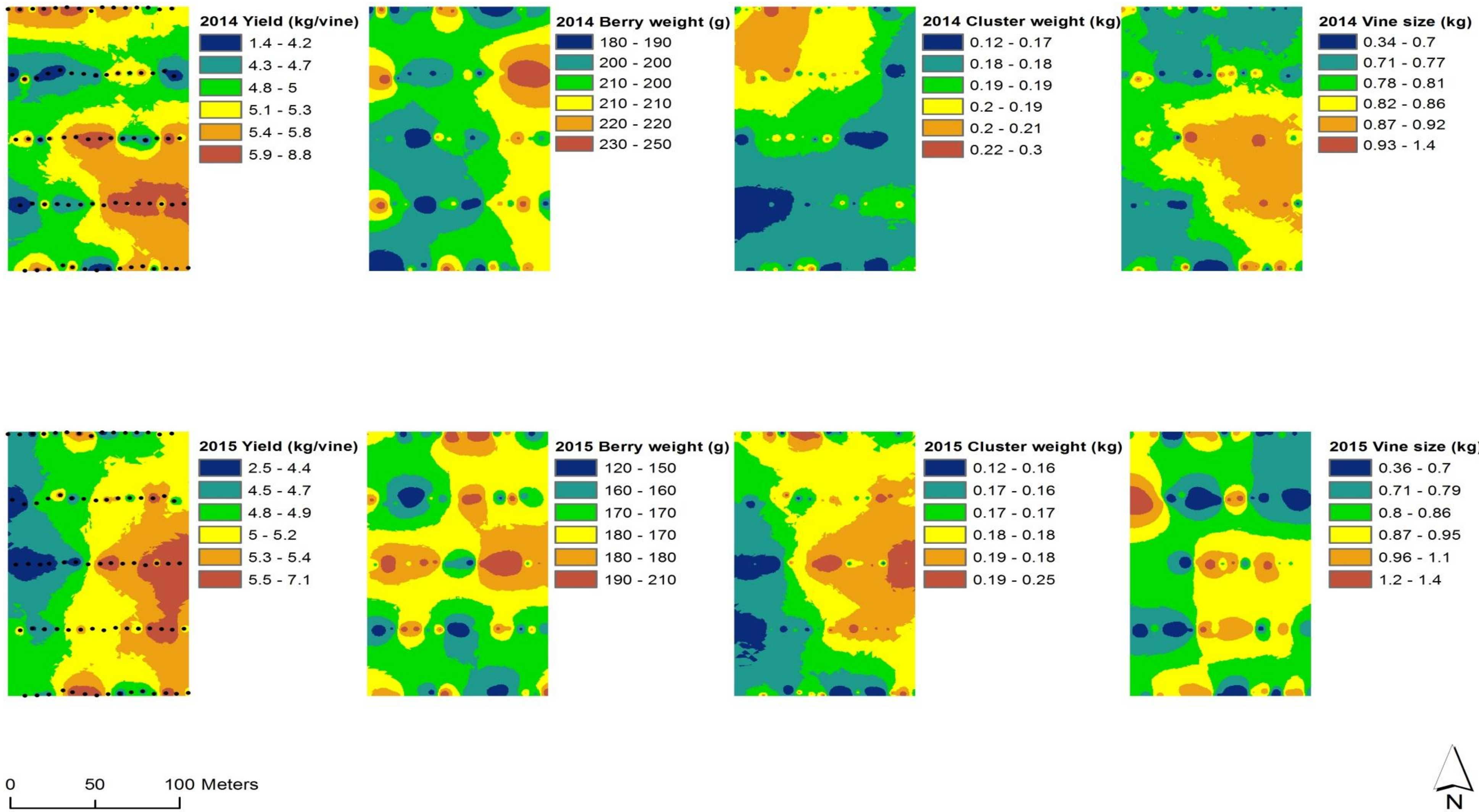

Figure A 25 Maps of yield (kg/vine), berry weight (g), cluster weight (kg), and vine size (kg/vine) for the Cave Spring Riesling in 2014 (top) and 2015 (bottom).

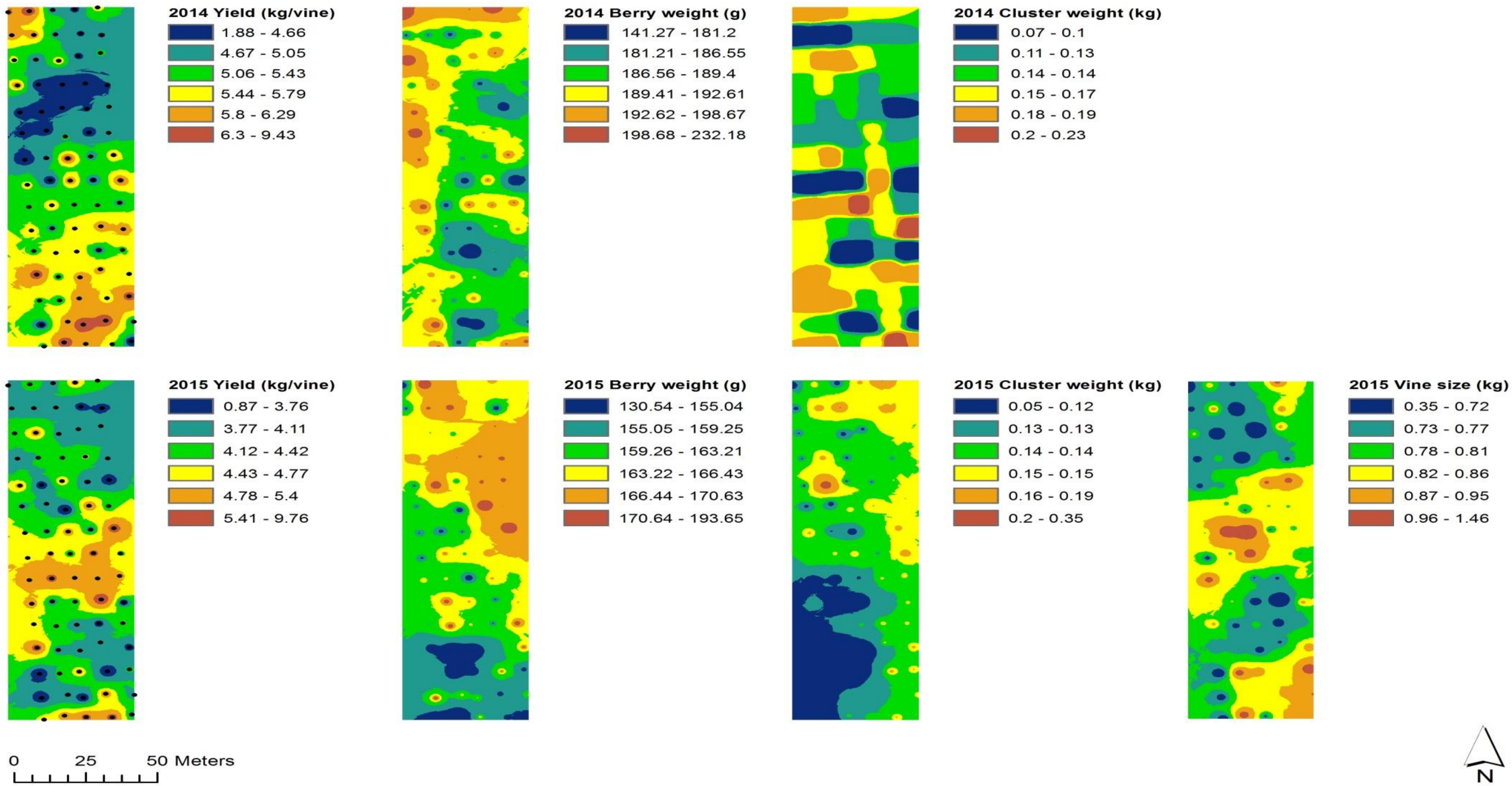

Figure A 26 Maps of yield (kg/vine), berry weight (g), cluster weight (kg), and vine size (kg/vine) for the Lambert Riesling in 2014 (top) and 2015 (bottom). Pruning weights were not collected in 2014.

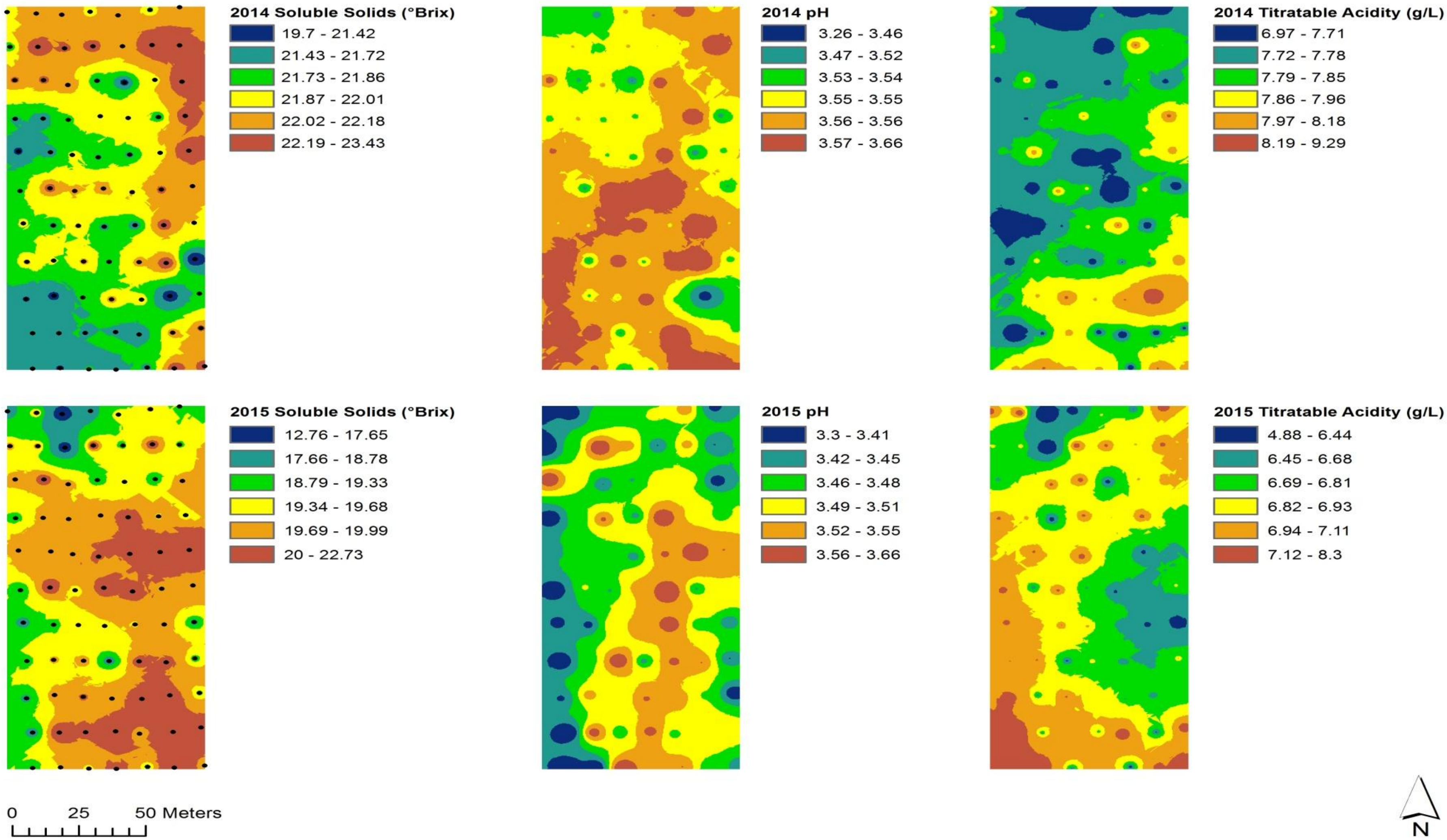

Figure A 27 Maps of soluble solids (°Brix), pH and titratable acidity for the Lambert Cabernet franc in 2014 (top) and 2015 (bottom).

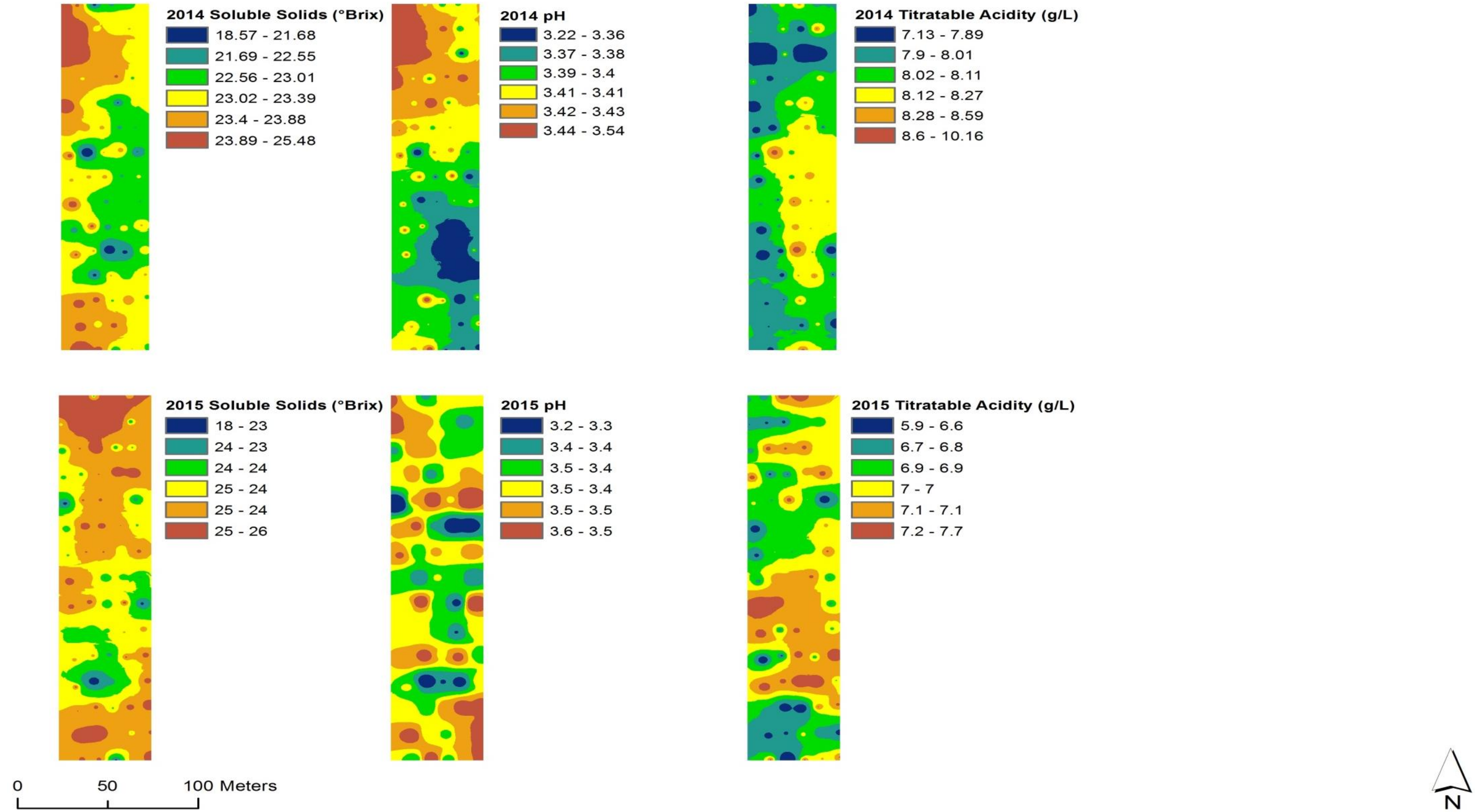

Figure A 28 Maps of soluble solids (°Brix), pH and titratable acidity for the Cave Spring Cabernet franc in 2014 (top) and 2015 (bottom).

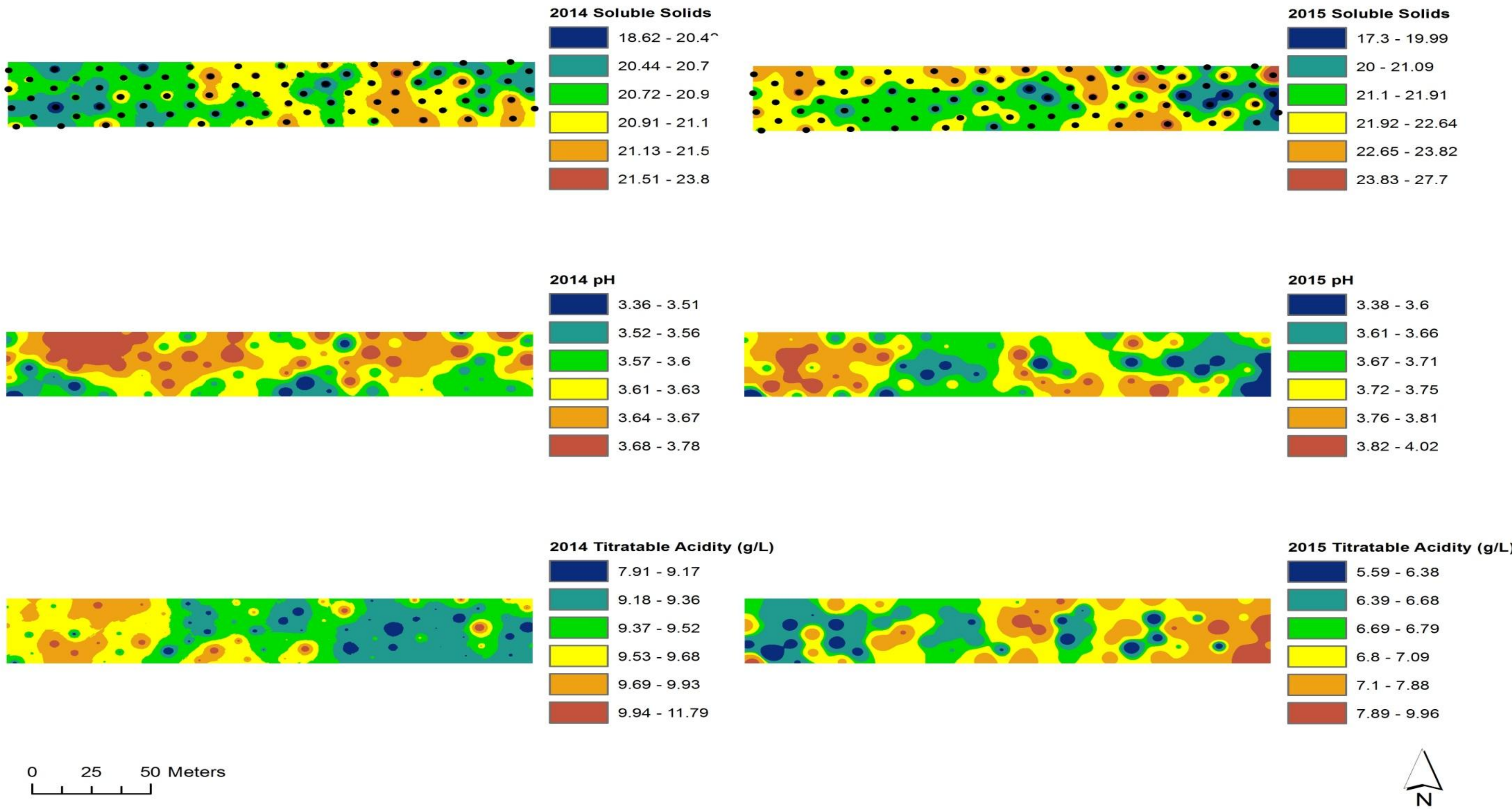

Figure A 29 Maps of soluble solids (°Brix), pH and titratable acidity for the Coyote's Run Pinot noir East-West in 2014 (left) and 2015 (right).

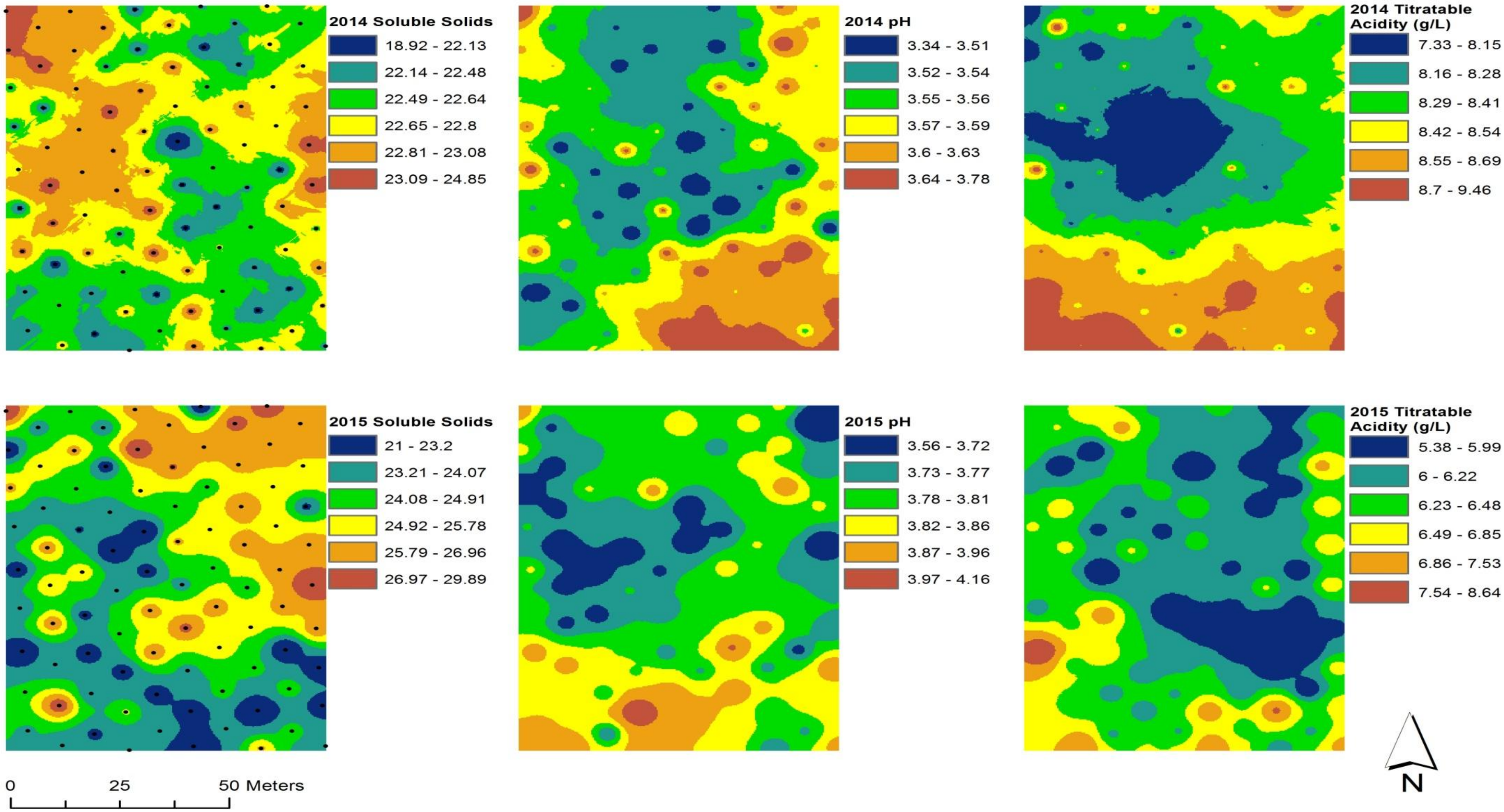

Figure A 30 Maps of soluble solids (°Brix), pH and titratable acidity for the Coyote's Run Pinot noir North-South in 2014 (top) and 2015 (bottom).

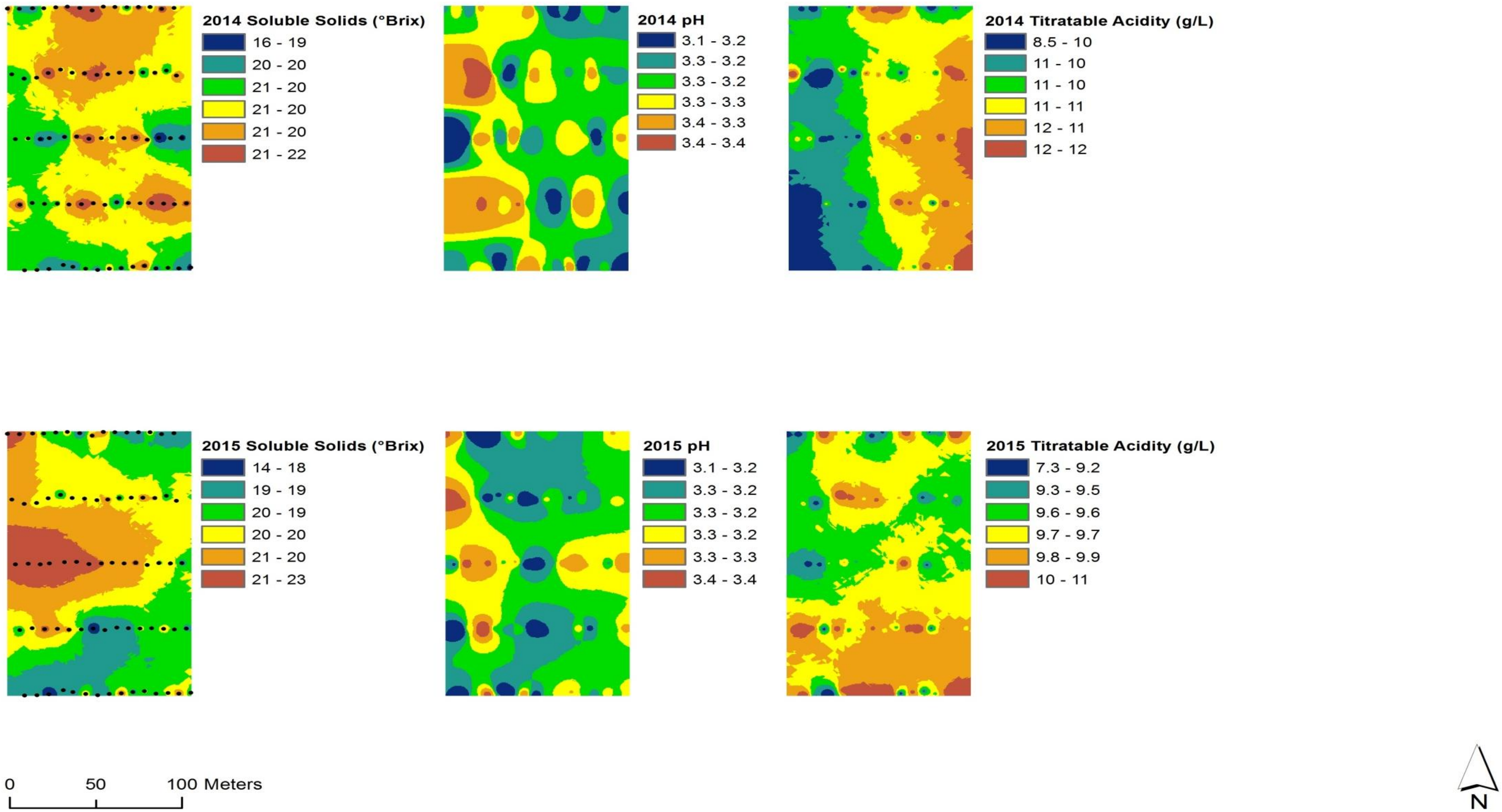

Figure A 31 Maps of soluble solids (°Brix), pH and titratable acidity for the Cave Spring Riesling in 2014 (top) and 2015 (bottom).

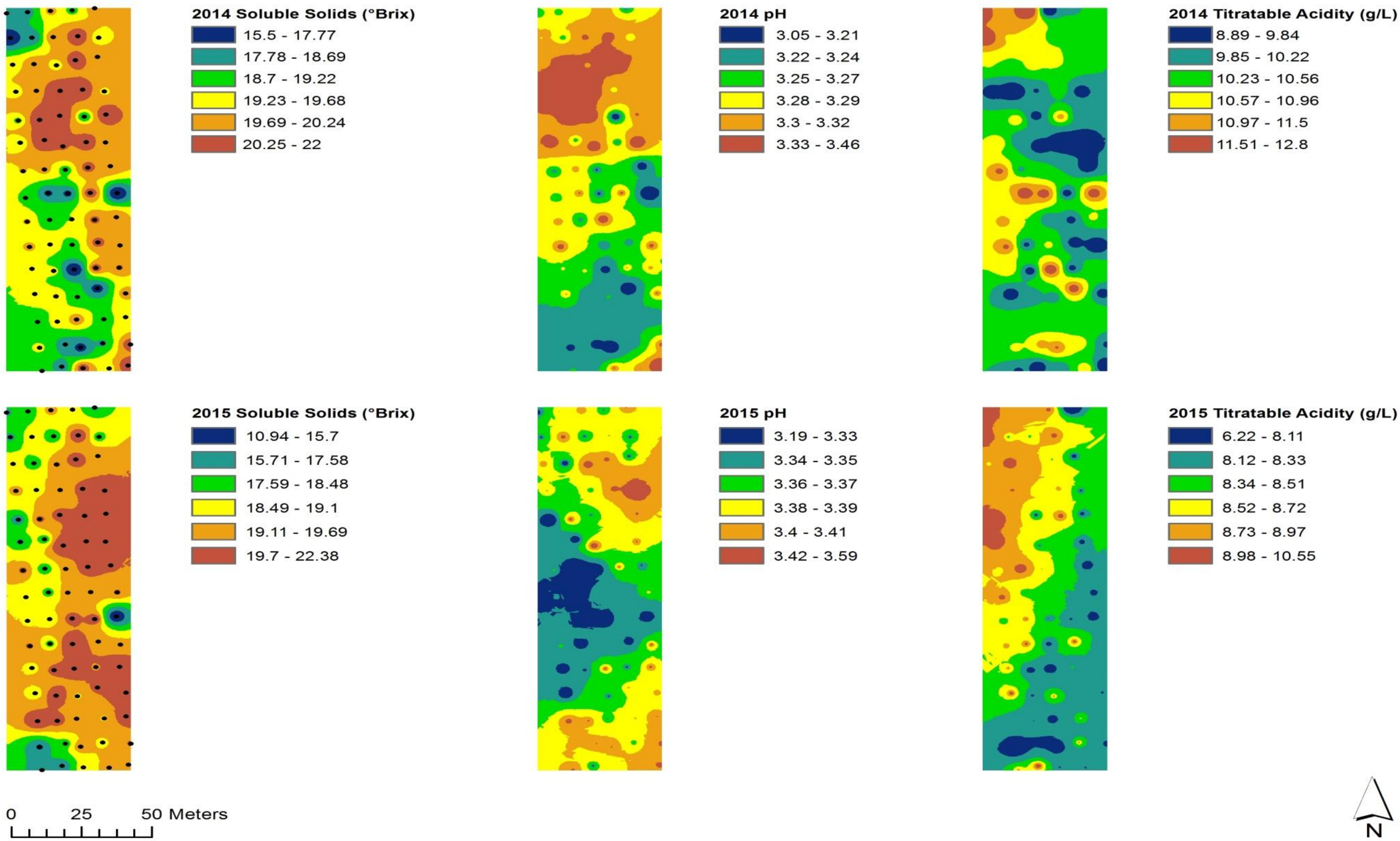

Figure A 32 Maps of soluble solids (°Brix), pH and titratable acidity for the Lambert Riesling in 2014 (top) and 2015 (bottom).

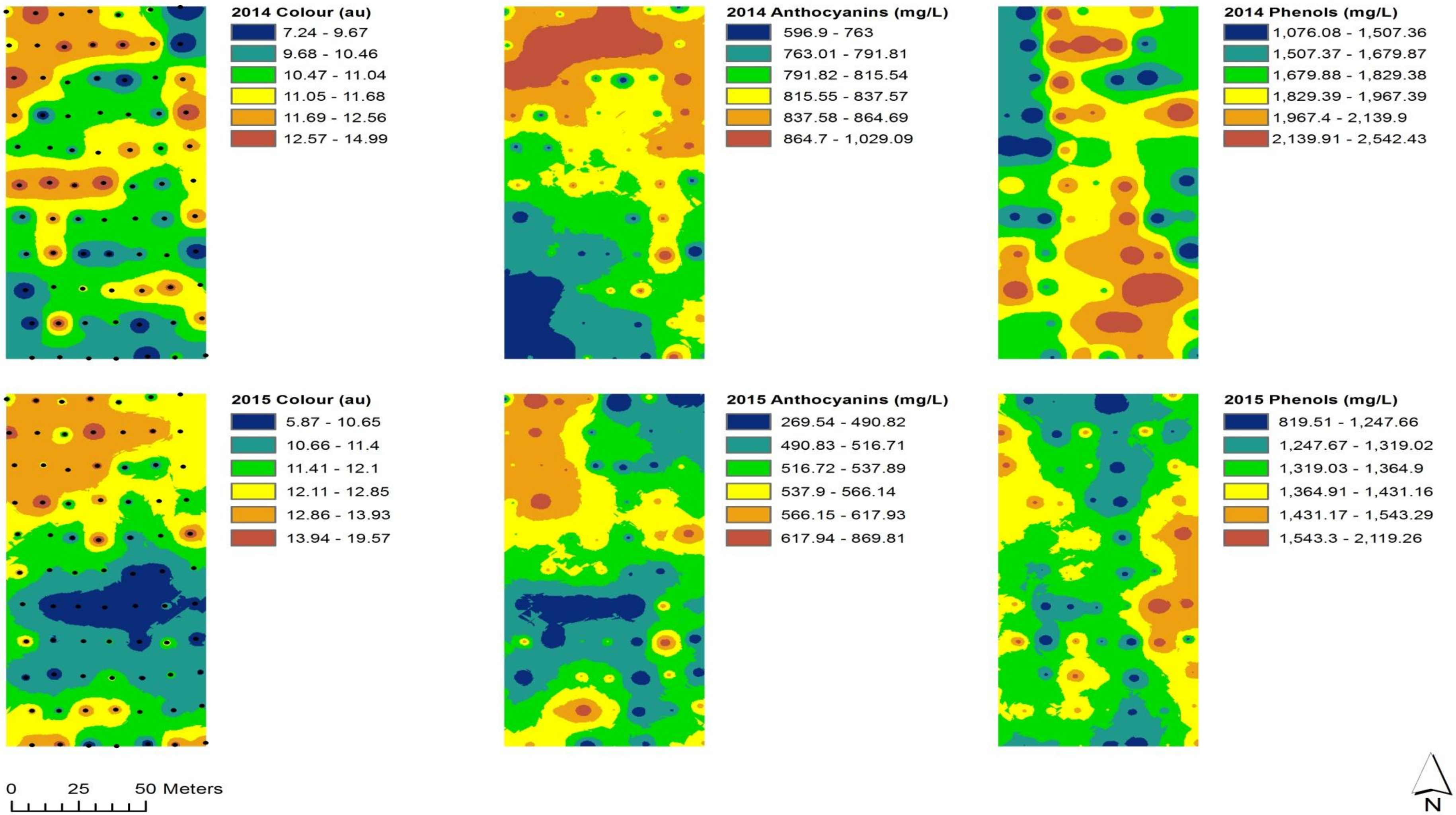

Figure A 33 Maps of colour (au), anthocyanins (mg/L) and phenols (mg/L) for the Lambert Cabernet franc in 2014 (top) and 2015 (bottom).

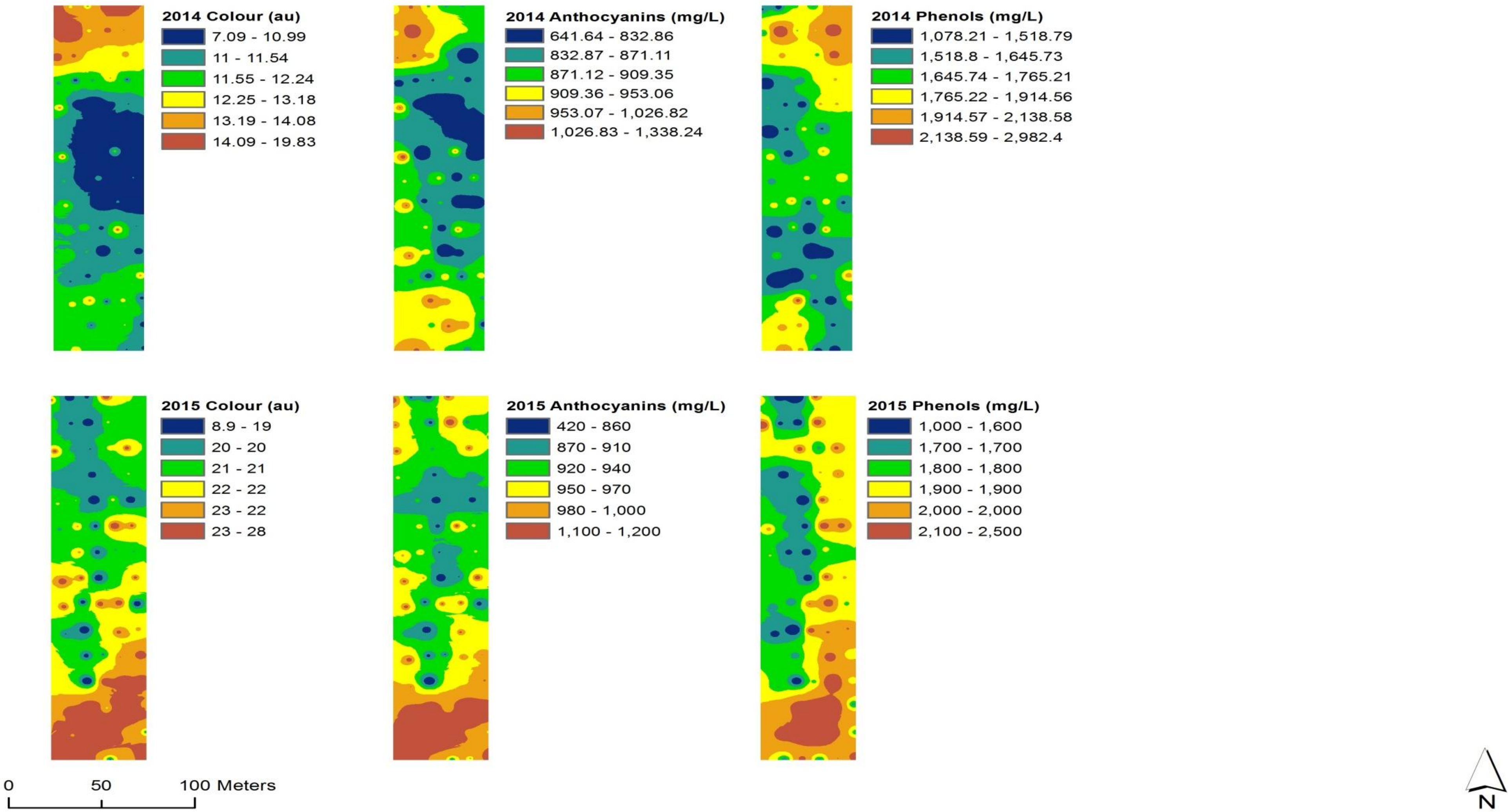

Figure A 34 Maps of colour (au), anthocyanins (mg/L) and phenols (mg/L) for the Cave Spring Cabernet franc in 2014 (top) and 2015 (bottom).

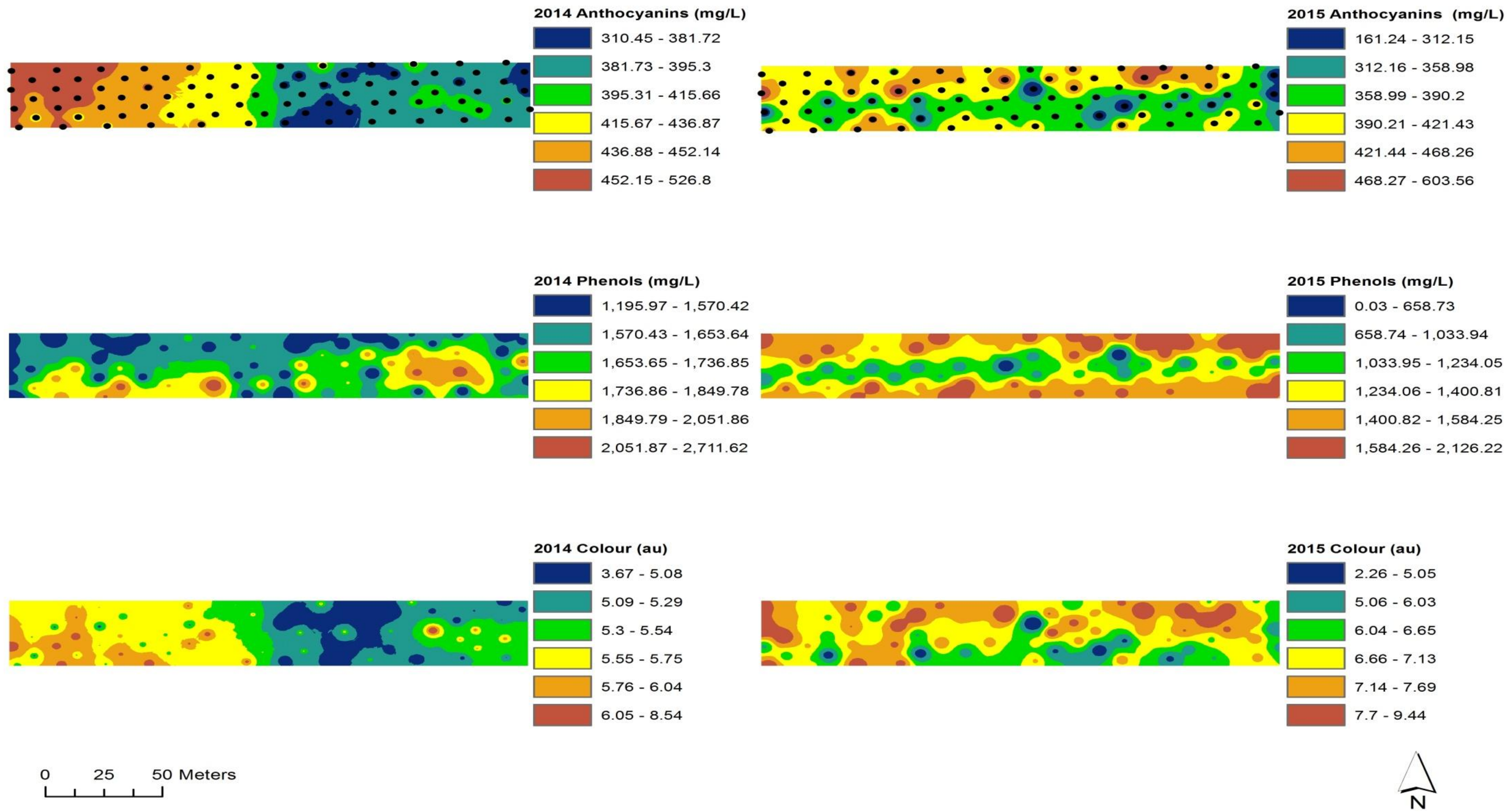

Figure A 35 Maps of anthocyanins (mg/L), phenols (mg/L) and colour (au) for the Coyote's Run Pinot noir East-West in 2014 (left) and 2015 (right).

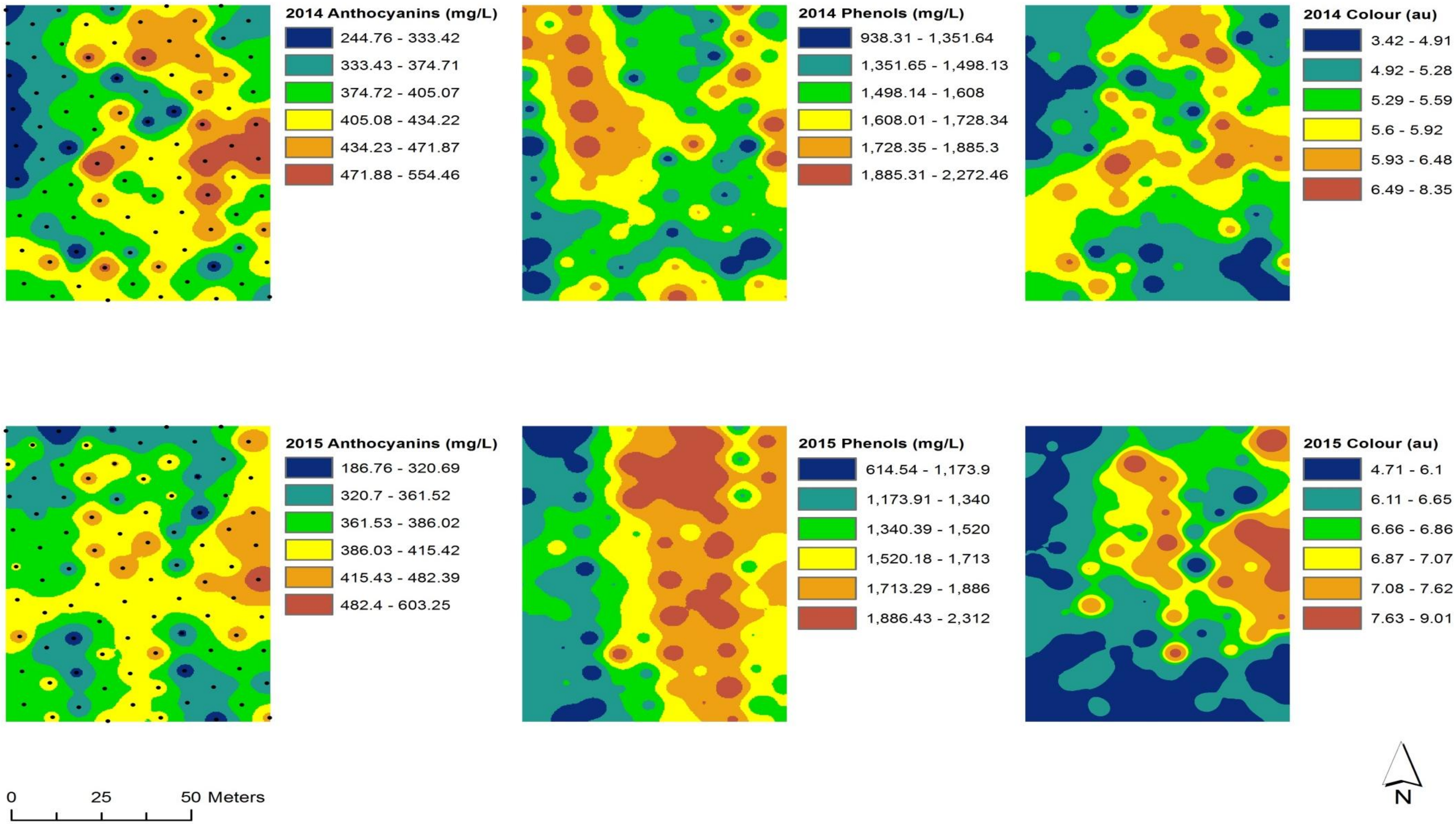

Figure A 36 Maps of anthocyanins (mg/L), phenols (mg/L) and colour (au) for the Coyote's Run Pinot noir North-South in 2014 (top) and 2015 (bottom).

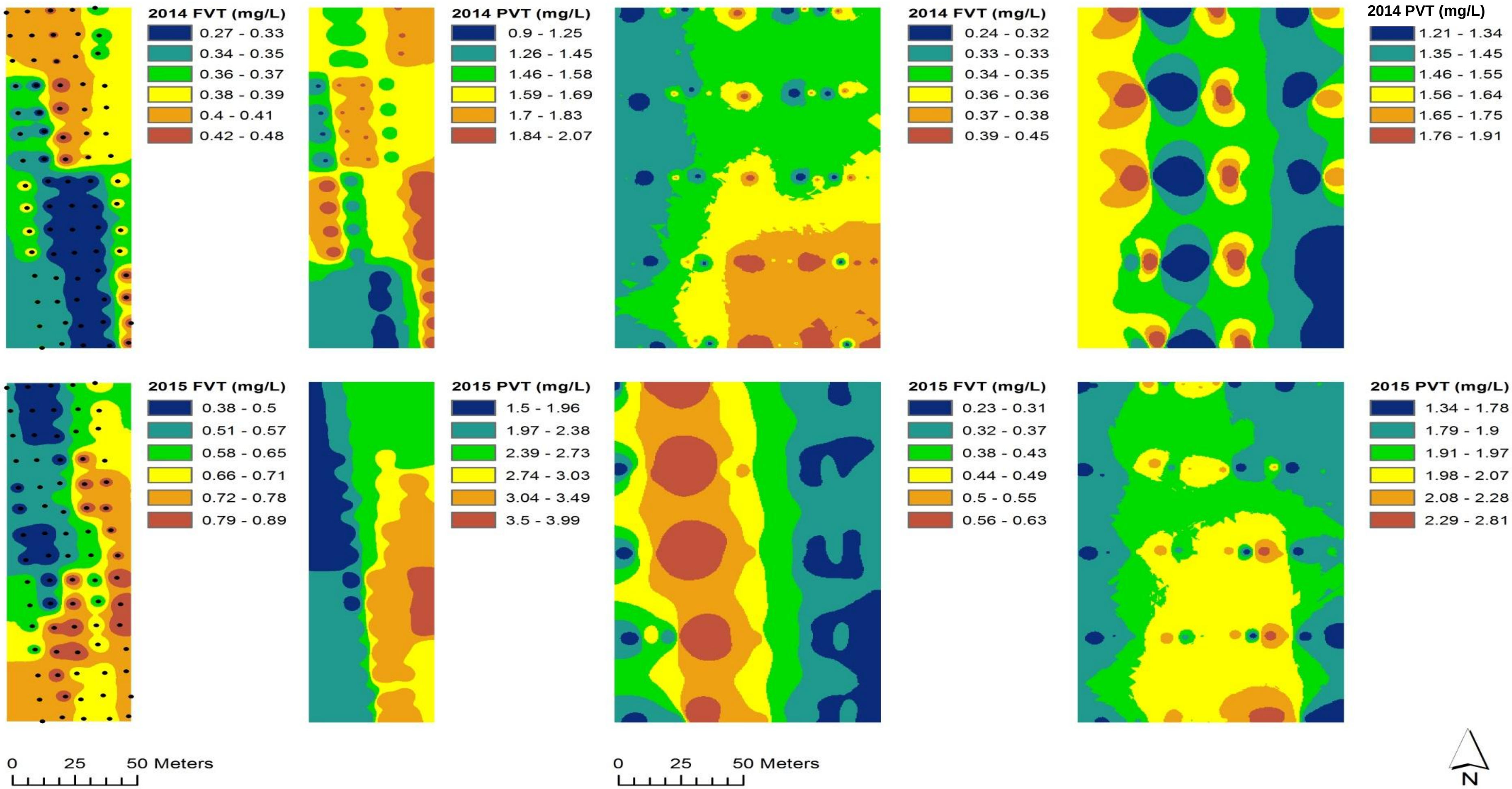

Figure A 37 Maps of the free volatile terpenes (FVT) and potentially volatile terpenes (PVT) for the Lambert Riesling (left) and Cave Spring Riesling (right) in 2014 (top) and 2015 (bottom).